Price Formation and Equilibrium Liquidity in Blockchains

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ABSTRACT

We study the effect of blockchain protocols on price discovery and liquidity in decentralised exchanges (DEXs). At regular intervals, traders bid *priority fees* to compete for queue position and better execution prices in the next block. In equilibrium, price discovery occurs at the same frequency as block creation, known as *block time*. Block time creates a tradeoff between price efficiency and liquidity supply in DEXs. Longer block times increase speculative rewards and encourage traders to pay the cost of information, which improves price efficiency. However, longer block time also deters liquidity supply, and results in market shutdown in the extreme. Priority fees transfer speculative profits from informed traders to validators, which increases liquidity supply, reduces trading costs for uninformed traders, and incentivises blockchain security. However, priority fees reduce price efficiency by limiting the number of traders who purchase information. Validation rewards mitigate the negative effects of priority fees and block time by improving price efficiency, increasing liquidity supply, and decreasing the likelihood of market shutdown.

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Acknowledgments: we are grateful to Bruno Biais, Patrick Chang, Joel Hasbrouck, Igor Makarov, and Andreas Park for their valuable comments and feedback. We are also thankful to participants of the CBER Conference at Columbia University, the Oxford-Harvard Conference at University of Oxford, the Stevens Institute of Technology's DeFi Seminar, and The SEEM Seminar at the Chinese University of Hong Kong for insightful discussions.

Blockchain technology and decentralised finance (DeFi) are profoundly reshaping the financial landscape (see Harvey (2016); Cong and He (2019)). The most prominent example of DeFi services are decentralised exchanges (DEXs) where significant volumes are traded daily on automated market makers (AMMs). DEXs are shaped by two key components: (i) the rules of the AMM, which determine the price of liquidity, and (ii) the consensus mechanism of blockchains, which governs the lifecycle of transactions.[1] AMMs are computationally simple and exist primarily because blockchains are unable to support infrastructures such as those that underpin current electronic exchanges. Yet, existing research primarily studies AMMs in isolation (see Lehar and Parlour (2021); Capponi and Jia (2021); Barbon and Ranaldo (2021); John, Kogan, and Saleh (2023)), and little is known about their microstructure within the infrastructure they are embedded in. A deeper understanding of DEX microstructure is essential to ensure fair and efficient markets, and to enable DeFi to fulfill its potential.

Blockchains are public ledgers where transactions are sequenced into blocks. Blocks are built at regular intervals called *slots*, and the duration of a slot is referred to as *block time*. Transactions are not immediately included in blocks but first enter a public *memory pool*. At the end of each slot, a block validator selects transactions from the memory pool, arranges the transactions in a particular order, and sequentially clears the market. Agents pay *priority fees* to validators to compete for queue position, and validators sequence transactions in blocks based on these fees.[2] Pending transactions in the memory pool are public, therefore competitive agents participate in *priority gas auctions* (PGAs) to optimise their orders' position in the queue and improve execution prices. This paper presents a model to describe price discovery, market frictions, and liquidity dynamics in DEXs. We show that blockchain mechanisms determine economic tradeoffs and incentives in DEXs. In particular, *priority fees* and *block time* are defining features of blockchains that fundamentally distinguish them from traditional electronic markets.

We model the strategic interactions between takers and suppliers of liquidity for a risky security in DEXs as a two-stage game. In stage one, a risk-neutral liquidity supplier sets the AMM's liquidity supply. In stage two, informed traders receive private information about the security's future value and take positions accordingly, both competing to buy or to sell the security. Trades executed in the AMM impact quoted prices, so losing priority to other informed traders in the block leads to adverse price impact, which increases with trading volume. Consequently, traders bid priority fees to compete for queue position. In equilibrium, traders determine the level of their priority fees and trading volumes, and the liquidity supplier determines the liquidity supply. To determine the priority fee they bid, traders balance the profits from better execution prices against the costs of paying the fee to the validator. To set the trading volume, traders balance increased profits from trading larger positions against execution costs and priority fees that increase with order size. To

[1] A blockchain transaction is any set of user-initiated instructions that modify the blockchain's global state. These include digital asset transfers between users, liquidity provision or taking in an AMM, smart contract deployment, and other state-changing operations. In this work, a transaction refers to a blockchain interaction, in contrast to traditional markets, where a transaction denotes a filled trade.

[2] In this paper, we do not use blockchain-specific terminology and refer to any blockchain operator involved in the block creation process as a validator.

set the AMM's liquidity depth, the supplier balances revenue from elastic and uninformed liquidity demand against anticipated expected losses to informed traders. In particular, these losses increase with the variance of informed traders' private signals, or equivalently, with the variance of their trading volumes. To study price efficiency, we analyse the equilibrium number of informed traders who, prior to the two-stage game, purchase information. This number is directly linked to price efficiency and is determined such that the marginal utility gain from being informed is negative, that is, when information costs exactly offset speculative profits and blockchain validation rewards.

Priority fees can only be revised upward in memory pools, and agents have one last opportunity to revise their priority fees before the creation of the block. We model this final phase as a first-price sealed-bid (FPSB) auction among informed traders. Any transaction with a nonzero priority fee submitted before the end of the slot acts as a reservation price for the final FPSB auction so it reduces the expected wealth of all traders. In equilibrium, transactions and private information are revealed only at the end of each slot, so price discovery in blockchains is periodic.[3] This is in contrast to the continuous rate of information dissemination in traditional electronic exchanges (see Kyle (1985b); Huddart, Hughes, and Levine (2001)).

Block time, combined with the structure of information dissemination in blockchains, creates opposing effects on price efficiency and liquidity supply. On the one hand, as block time increases, more liquidity demand accumulates, which increases revenue for liquidity suppliers and encourages greater supply. This, in turn, raises the volumes informed traders wish to trade and drives priority fees up. On the other hand, longer block times provide more time for changes in the fundamental price of the risky security, increasing the variance of private signals and expected speculative profits. This encourages more traders to pay the cost of information and improves price efficiency, however, it also causes defensive reductions in supply. When block time exceeds a threshold, liquidity suppliers are deterred from entering the market, so markets shut down. This threshold increases in the aggregate level and the elasticity of liquidity demand. This prediction mirrors that in Glosten and Milgrom (1985), where there are no bid and ask prices if the signals of informed traders are too precise relative to the elasticity of liquidity demand, preventing liquidity suppliers from breaking even (see also Bhattacharya and Spiegel (1991)).

Priority fees and trading volumes are publicly observable on the blockchain and constitute a vehicle for price discovery, so a large number of informed traders improves price efficiency. In DEXs, priority fees discourage traders from paying information costs, reducing price efficiency. Blockchain validation rewards mitigate this effect. More precisely, the cost of acquiring information in DEXs include running a blockchain node, so informed traders can also become validators. As a result, validation rewards improve price efficiency by compensating for the losses in priority fees. In equilibrium, although these rewards encourages more speculation, the competition and uncertainty effects of PGAs reduce informed traders' overall trading volumes, leading to deeper liquidity and lower costs for uninformed liquidity demanders. In particular, the threshold for block time beyond which

[3]Existing work compares the microstructure of DEXs to that of traditional exchanges (see Barbon and Ranaldo (2021); Aoyagi and Ito (2021)) without accounting for these effects and those of priority fees.

markets shut down increases with the number of informed traders competing in the memory pool. Finally, priority fees are speculative revenue transferred to validators to operate the blockchain, so DEXs do not impose explicit infrastructure costs on uninformed traders and liquidity suppliers. This contrasts with traditional exchanges where all participants bear infrastructure costs such as order handling fees (Stoll (2003); Biais, Glosten, and Spatt (2005)).

Our work is related to the literature on preopening and closing auctions in traditional markets. There are fundamental differences between the purpose and mechanics of these sessions and those of blockchain slots. Preopening sessions are uniform price auctions (Budish, Cramton, and Shim (2015)), where clearing prices maximise trading volume, and agents observe partial information (Van Bommel and Hoffmann (2011)). In contrast, priority gas auctions feature discriminatory pricing subject to queue ordering, and they are publicly visible. Despite these differences, similarities exist. Like memory pools, opening sessions do not clear markets until a specific time, and agents can communicate with one another. Our findings support the *pure-noise hypothesis* of Biais, Hillion, and Spatt (1999), which posits that trading activity before the end of preopening sessions does not contain new information. Additionally, our results are empirically supported by Medrano and Vives (2001), who find that information dissemination accelerates toward the end of preopening sessions (see also Cao, Ghysels, and Hatheway (2000); Davies (2003)). Our model for PGAs is also related to online auctions with hard closing times, such as those run by eBay. Our results align with empirical findings (Roth and Ockenfels (2002); Yang and Kahng (2006)) which show that late bidding is significant in these auctions.

Our model is related to the microstructure literature that studies the properties of price and liquidity in traditional electronic exchanges. We extend these approaches to account for the unique mechanics of DEXs. Unlike traditional markets, where orders execute continuously if liquidity is available and traders compete on speed (O'Hara (1998)), blockchains clear periodically at fixed intervals and traders compete for queue position with priority fees. Biais (1993); De Frutos and Manzano (2002) study market properties with a two-stage inventory-based model where dealers compete for public order flow. In contrast, blockchain-based liquidity supply accumulates in a common pool, determining the price of liquidity and revenue which is equally shared among all suppliers. As a result, equilibrium outcomes are primarily driven by competition among traders. Our model is also related to the theory on information processing costs such as that in Grossman and Stiglitz (1980), Verrecchia (1982), and Kyle (1989).

Some studies examine periodic uniform price auctions for market clearing (Madhavan (1992); Budish et al. (2015)), and they show that these auctions enhance price efficiency but impose higher information costs on traders. Instead, our model considers discretionary, public auctions in which liquidity suppliers do not participate. Moreover, much of the microstructure literature assumes an information monopolist (Kyle (1985a)). In blockchains, monopolistic information would drive priority fees to zero in equilibrium, which contradicts empirical evidence showing that priority fees increase with the informational content of transactions Capponi, Jia, and Yu (2024). Competition among multiple informed traders, as in Holden and Subrahmanyam (1992) and Foster and

Viswanathan (1996), leads to an instantly revealing equilibrium where prices fully reflect private information. Our model mirrors this result, as traders submit fully revealing priority fees. However, blockchains operate with periodic clearing, so the revealing equilibrium is delayed until the end of block time.

Numerous works explore the microstructure of AMMs. Angeris, Evans, and Chitra (2021); Capponi, Iyengar, Sethuraman, et al. (2023a); Milionis, Moallemi, Roughgarden, and Zhang (2022); Cartea, Drissi, and Monga (2023, 2024a) show that AMMs cause losses to liquidity suppliers. Lehar and Parlour (2021) describe competition between AMMs and order books. Hasbrouck, Rivera, and Saleh (2022) show that higher fees in AMMs increase liquidity supply and decrease trading costs. Park (2023) studies the different types of cost when trading in AMMs. Hasbrouck, Rivera, and Saleh (2023) study concentrated liquidity AMMs. Malinova and Park (2024) examines the potential of AMMs in equity markets. Capponi et al. (2024) studies the influence of gas fees on the informativeness of trades in AMMs. Cartea, Drissi, Sánchez-Betancourt, Siska, and Szpruch (2024b) propose AMM designs to mitigate losses of liquidity suppliers. In contrast to this literature, we study DEXs as the interplay of AMMs and the blockchain on which they operate.

Crypto-assets and blockchain economics attract attention in the literature (Biais, Capponi, Cong, Gaur, and Giesecke (2023b)). Cong, Li, and Wang (2021) analyse the adoption of digital platforms. Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2023a) study the drivers of cryptocurrency prices and risks. Cong, Hui, Tucker, and Zhou (2023) study the economic implications of *layer-2* blockchains. Harvey and Rabetti (2024) explore how investors and regulators engage effectively with DeFi. Finally, the applications of DeFi extend beyond DEXs. They include central bank digital currencies (Fung and Halaburda (2016); Auer, Frost, Gambacorta, Monnet, Rice, and Shin (2022)), cross-border settlement (Harvey (2021); Hub (2023); Cardozo, Fernández, Jiang, and Rojas (2024)), and asset tokenisation (Heines, Dick, Pohle, and Jung (2021)).

The remainder of this paper proceeds as follows. In Section I, we outline the key features of AMMs and blockchains relevant to describe DEX microstructure. In Section II, we present notation, assumptions, and structure of the model. In Section III, we study the priority fee bidding strategies and trading volumes of informed traders. In Section IV, we analyse the liquidity supply. In Section V, we study price efficiency when information is costly. Finally, Appendix A describes the mechanics of PGAs in the Ethereum blockchain and Appendix B collects the proofs.

I. Blockchains and automated market makers

Price formation in DEXs arises from the interplay between blockchain protocols and the mechanisms of AMMs. Blockchain protocols govern the lifecycle of transactions from submission to execution. They dictate how information disseminates to the market prior to execution and they determine infrastructure costs, including gas fees paid to validators who ensure network security. On the other hand, AMM mechanisms define the rules of interaction between liquidity takers and suppliers. They determine the price of liquidity and adjust prices based on trading activity.

The microstructure of DEXs differs fundamentally from that of traditional financial markets. Accurately describing its properties requires modelling the key elements in both the blockchain protocol and the AMM mechanism. In what follows, we outline the defining features of these components, which underpin the framework of our model.

A. Blockchains

Here, we describe the key elements of blockchain infrastructure relevant to our model. A blockchain is a distributed digital ledger stored by participants—referred to as nodes—within a public network. Any entity can be a node and maintain a copy of the ledger. For a transaction to be executed on the blockchain, it must be included in a block created by a *validator*. Blocks are sequentially added to the ledger at regular intervals called *slots*, the duration of which is referred to as *block time*. For example, the current block time in Ethereum, the main blockchain hosting the most liquid DEXs, is 12 seconds. Block time must be long enough to allow for secure and robust confirmation of blocks, a process that requires aggregating a large number of cryptographic signatures in multiple rounds of network communications. Shortening block time excludes slower participants and concentrates rewards among those with superior connectivity, undermining decentralisation. Thus, block time is a buffer that balances security and decentralisation.

All blockchain activity is publicly visible. When an agent submits a transaction, it is not immediately included in a block. Instead, the transaction is broadcast to nodes in the network and stored in their local memory, known as the *memory pool*. The transaction propagates through the network until it is visible to all nodes. The block validator, randomly selected at each slot by the blockchain protocol, selects transactions from their memory pool to create the next block. validators are paid *gas fees* by agents to include their transactions in the block.

Gas fees consist of two components: the base fee and the priority fee. The base fee is paid to all nodes and is mandatory for inclusion in a block. Base fees are sized by the blockchain to regulate network traffic. In contrast, the priority fee is optional, paid exclusively to the validator, and incentivises transaction inclusion and queue priority in the block. Transactions in the memory pool are public, so agents observe the pool's state and adjust their gas fees or resubmit transactions to gain queue priority. This *pre-trade transparency* leads to "priority gas auctions" (PGAs), where agents pay priority fees to compete for better queue positions and for better execution prices. PGAs are fundamental to the microstructure of DEXs, so one must consider these costs, and the incentives it creates, in models of these markets. For additional details on blockchain protocols, see John, Monnot, Mueller, Saleh, and Schwarz-Schilling (2025).

Finally, validators have great latitude in deciding which transactions to include and in what order, including their own transactions. Ethereum builders, for example, exploit this flexibility to extract revenue through transaction ordering, a practice referred to as miner extractable value (MEV). MEV and PGAs create costs for trading agents, who can choose to bypass public memory pools and submit transactions directly to a specific validator. Our model excludes MEV extraction by validators, as blockchain designers actively seek to eliminate it, for instance with layer-2

blockchains; see Sguanci, Spatafora, and Vergani (2021); Gangwal, Gangavalli, and Thirupathi (2023). Similarly, we do not consider private memory pools or transactions, because they are not frequently used; see Piet, Fairoze, and Weaver (2022).

B. Automated Market Makers

The second key determinant of DEX microstructure is the AMM. In this section, we outline market frictions and wealth considerations for liquidity takers and suppliers, which are relevant to our model. In AMMs, rules specify how liquidity supply, in the form of aggregated reserves in a liquidity pool, determines execution prices and price impact; see Lehar and Parlour (2021),Capponi and Jia (2021), and Cartea, Drissi, and Monga (2022).

Liquidity takers in DEXs. Assume trading is conducted in an AMM that supplies liquidity x_0 in the reference security X and y_0 in the risky security Y. A trading function Φ, known to all market participants, defines the combinations of reserves $\{x = \Phi(y), y\}$ that make liquidity suppliers indifferent, i.e., an iso-liquidity curve. This has the following implications for liquidity takers. Let $\delta > 0$ denote a quantity of security Y that a trader wishes to buy (resp. sell), for which the trader pays (resp. receives) the amount $\Phi(y_0 - \delta) - \Phi(y_0)$ (resp. $\Phi(y_0 + \delta) - \Phi(y_0)$) in security X. Thus, the execution prices per unit of the risky security are

$$\text{price to sell } \delta: \quad \frac{\Phi(y_0) - \Phi(y_0 + \delta)}{\delta}, \qquad \text{price to buy } \delta: \quad \frac{\Phi(y_0 - \delta) - \Phi(y_0)}{\delta}, \tag{1}$$

so the execution prices for an infinitesimal volume $\delta \to 0$ converge to $V_0 = -\Phi'(y_0)$, which we refer to as the *marginal price* of security Y in terms of X, or simply the price of security Y.

The marginal price is a reference price, and the difference between execution prices and marginal prices represent execution costs. This is similar to the difference between the mid-price in a limit order book and the execution price obtained from matching resting limit orders, or the difference between the fundamental price in an over-the-counter market and the bid/ask prices quoted by dealers; see Kyle (1985b); Biais (1993) for more details. In AMMs, the reserves y_0 in the pool determine execution costs, which we define as the difference between the price V_0 and the execution prices in (1). The reserves also determine the impact of a liquidity taking trade on the price. In our models below, the buy and sell prices, per unit of security traded, are

$$\begin{aligned} \text{price to sell } \delta: \quad & \frac{\Phi(y_0) - \Phi(y_0 + \delta)}{\delta} \approx V_0 - \frac{1}{2}\,\delta\,\Phi''(y_0)\,, \\ \text{price to buy } \delta: \quad & \frac{\Phi(y_0 - \delta) - \Phi(y_0)}{\delta} \approx V_0 + \frac{1}{2}\,\delta\,\Phi''(y_0)\,. \end{aligned} \tag{2}$$

Similarly, the impact on the price following a trade of volume δ is

$$\begin{aligned} \text{impact after the sell order}: \quad & -\Phi'(y_0 + \delta) - V_0 \approx -\delta\,\Phi''(y_0)\,, \\ \text{impact after the buy order}: \quad & -\Phi'(y_0 - \delta) - V_0 \approx \delta\,\Phi''(y_0)\,. \end{aligned} \tag{3}$$

Equations (2) and (3) consider a second and first-order approximation of execution costs and price impact. The term $\frac{1}{2}\,\delta\,\Phi''(y_0)$ in the execution prices in (2) is akin to the difference between (i) the volume-weighted average price received by a trader and (ii) the mid-price in a limit order book. Figure 1 shows that our approximations hold in practice.

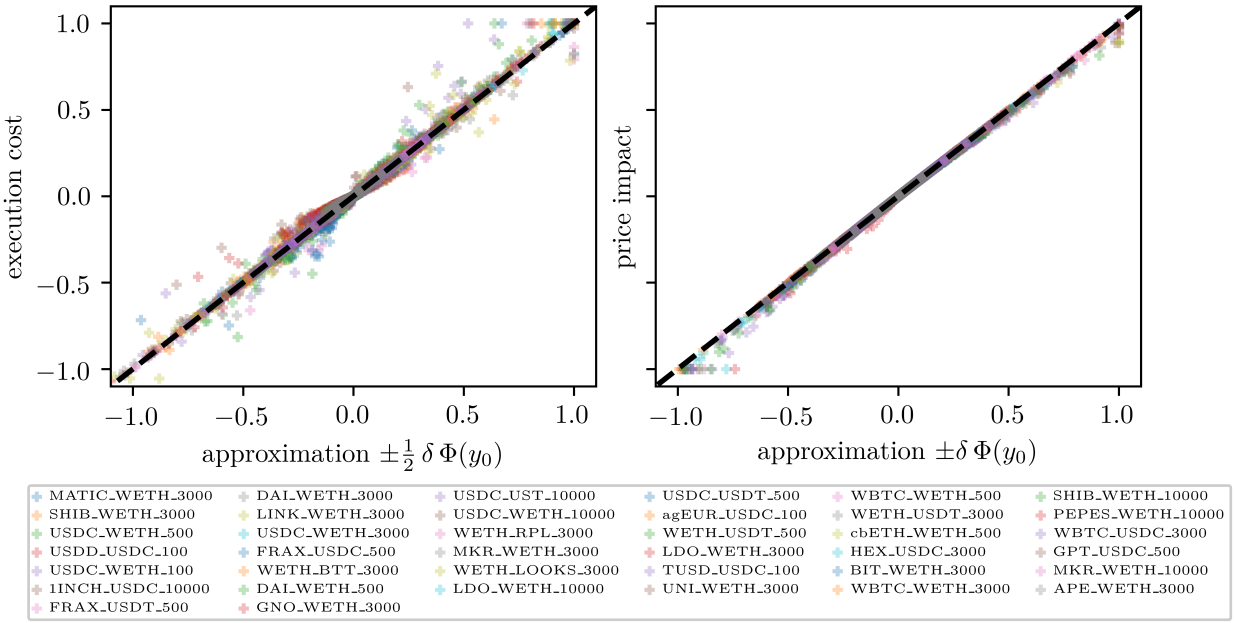


Figure 1. Scatter plots of the execution cost and the price impact of 2.622 million LT transactions against the approximations (2) and (3). The transactions are between 1 January 2023 and 31 December 2023 in 38 different Uniswap V3 pools. For each pool, the execution costs and price impacts are scaled between $[0, 1]$ for buy orders and $[-1, 0]$ for sell orders.

The convexity Φ'' of the trading function is key to determine trading frictions, i.e., execution costs and price impact, when the supply of liquidity is limited. In AMMs, the convexity is inversely proportional to the size of the pool, and we refer to

$$\kappa = 2/\Phi''(y_0) \tag{4}$$

as the *depth of liquidity*.[4] Thus, execution costs in (2) are given by δ/κ. Akin to traditional electronic markets, execution costs and price impact, defined in (2) and (3), increase with the traded volume δ and decrease with the depth of liquidity.

The depth of liquidity κ determines execution costs and price impact of liquidity taking trades, and thus it influences the execution prices of subsequent trades in the pool. In PGAs within memory pools, informed traders compete for block priority to avoid potentially worse execution prices caused by the price impact of preceding orders in the block. For instance, assume that two traders consecutively buy an amount δ of security Y. Using the formula for execution costs in

[4]For example, the trading function for constant product markets like Uniswap, which are the most popular DEXs, is $\Phi(y) = \kappa^2/y$ so $k = 2\,V_0^{3/2}/\kappa \implies \kappa = 2/k = y_0$.

(2) and price impact in (3), the execution price for the trader with queue priority in the block is $V_0 + \delta/\kappa$, after which the new price updates to $V_1 = V_0 + 2\,\delta/\kappa$. Consequently, the execution price for the trader without queue priority is $V_1 + \delta/\kappa = V_0 + 3\,\delta/\kappa$.

Liquidity suppliers in DEXs. In our model, liquidity supply is determined endogenously. Assume that a representative liquidity supplier sets a pool with depth κ and that the marginal price implied by the pool's reserves is V_0. Next, assume the future liquidation value of security Y is V, and that the total volume traded in the pool δ adjusts the future marginal price $-\varphi'(y_0 + \delta)$ to V. Let $y = y_0 + \delta$ denote the AMM's reserves when the price of the security is V, and let π denote the fixed proportional fee charged by the pool.

LEMMA 1: *By no-arbitrage, the trading function of the AMM is convex. Additionally, the change ΔW_L in the wealth W_L of the liquidity supplier is given by*

$$\Delta W_L = y_0\ (V - V_0) - \big(\Phi(y_0) - \Phi(y) - \Phi'(y)(y_0 - y)\big) + \pi\,\delta\,, \tag{5}$$

when the marginal price in the AMM shifts from V_0 to V as a result of a liquidity taking order of size δ. The second term in (5) *is always nonpositive because of the necessary convexity of Φ.*

The change in the wealth of the liquidity supplier can be interpreted as follows. The first term on the right-hand side of (5) represents the change in wealth had the initial reserves y_0 been held outside the pool. The second term in (5) is an adjustment due to the change in value of reserves when traders transact δ. This term, commonly referred to as *impermanent loss*, reflects the impact of informed trading on the LP's wealth. The last term on the right-hand side of (5) represents the fee revenue from the LT's trade.

In our model below, we approximate the loss from supplying liquidity with

$$-\big(\Phi(y_0) - \Phi(y) - \Phi'(y)(y_0 - y)\big) \approx -\frac{1}{2}\,\Phi''(y)\,(y - y_0)^2 = -\delta^2\,/\kappa, \tag{6}$$

where κ is the depth of the AMM's liquidity. Intuitively, and akin to traditional markets, the impermanent loss (6) is nonpositive because liquidity providers receive more reserves of the security whose price has decreased and less reserves of the security whose price has increased. More precisely, after a liquidity-taking trade of size δ, the LP earns revenue δ/κ due to execution costs in (2), while incurring adverse selection costs $-2\,\delta/\kappa$ due to price impact in (3).

The economic incentives for liquidity supply in AMMs are similar to those in market making within limit order books and dealer markets, and many insights from classical models apply (e.g., Ho and Stoll (1983), Glosten and Milgrom (1985)). Moreover, the trading function of an AMM can be viewed as a parameterised price schedule in electronic exchanges; see Glosten (1994); Biais, Martimort, and Rochet (2000). As a consequence, while our model assumes trading occurs within an AMM, similar conclusions apply to other blockchain-based markets.

II. The model

We study the microstructure of DEXs, which is determined by the combined effects of blockchain and AMM mechanisms. The features of the model are discussed first and our results follow.

A. General features

Consider a DEX for a risky security Y and a reference security X. There are three types of agent, a representative liquidity supplier (he) who deposits assets in a liquidity pool, informed traders (she), and uninformed liquidity traders with elastic demand (they). More precisely, two informed traders hold private information about the future liquidation value of the security. Each trader submits priority fees to compete for queue priority in the next block. In contrast, uninformed liquidity traders do not bid priority fees strategically, so they pay the base fee only, which we set to zero without loss of generality. The liquidity supply in the DEX, and the subsequent trading process, both in the memory pool and in the liquidity pool, are modelled as a game which proceeds as follows.

- *Stage one*: the liquidity supplier submits a transaction, which is included in a given block, to set an AMM with liquidity depth κ. Setting the depth κ is equivalent to determining the quantity of reserves to deposit in the liquidity pool.
- *Stage two*: following the creation of the previous block, a new blockchain slot begins. Informed traders observe private information about the liquidation value V of the security, after which each trader determines her priority fee bidding strategy and trading volume. The PGA is an online (English) auction with a hard close at the end of the blockchain slot. Additionally, liquidity traders submit transactions to the memory pool without priority fees.
- At the end of the slot, corresponding to block time, a new block is created with transactions ordered according to the level of priority fees. Specifically, the block incorporates the transactions of informed traders first, followed by those from uninformed liquidity traders who only pay the base fee. The final liquidation value of the security is then realised, resolving any remaining uncertainty.

After the liquidity supplier sets the pool, we assume for simplicity that the liquidity supplier does not compete with informed liquidity takers for queue position in the next block. This modelling assumption is motivated by the passiveness of liquidity supply in AMMs and blockchains, where the active management of liquidity positions is impractical due to excessively high gas costs. As described below, the liquidity supplier's strategy depends indirectly on the behaviour of informed traders; she chooses the depth κ based on rational expectations regarding the traders' trading volumes. Our model mirrors the structure of microstructure models for traditional electronic exchanges, where rounds of trading occur with sequential decisions from different types of market participants.

At the start of the slot, both informed traders know whether the liquidation value V of the security after the creation of the block will be greater or less than V_0, determining whether both

of them are buyers or sellers. Also, each trader receives a private signal about V, drawn from a common and known distribution. At the end of the slot, the order of the trader with the highest priority fee is executed first in the block, followed by the other trader's order. Subsequently, the block processes the orders of uninformed liquidity traders.

The equilibrium of this game is solved by backward induction. At the second stage, given some level of liquidity depth, the bidding strategies and trading volumes are determined. At the previous stage, the liquidity supply κ is determined based on the liquidity supplier's rational expectations of the trading volumes of informed traders and the uninformed liquidity traders' activity.

B. The Assumptions

The sequence of events is described in more detail below and is illustrated in Figure 2.

***Stage one*: liquidity supply.** At stage one, a risk-neutral representative liquidity supplier sets an AMM pool with depth κ to balance losses to informed traders with fee revenue earned from liquidity traders. Recall that π denotes the fixed proportional fee charged by the pool, and let $V_0 = 0$ be the initial price of security Y in the AMM; see Lehar, Parlour, and Zoican (2024) for a detailed analysis of the implications of fixed proportional fees on the microstructure of AMMs.

Liquidity traders transact a net volume that sums to zero but an absolute volume which we assume is elastic. Specifically, the liquidity demanded by buyers is linear in the price $V_0 + 1/\kappa$ (see (2)):

$$\frac{N}{2}\ (1 - \theta/\kappa)\ ,$$

and the liquidity demanded by sellers is linear in the price $V_0 - 1/\kappa$:

$$-\frac{N}{2}\ (1 - \theta/\kappa)\ .$$

The demand for liquidity at the ask (resp. bid) is characterised by two parameters: $N/2$, which represents the aggregate of all uninformed liquidity traders' private positive (resp. negative) liquidity needs throughout the blockchain slot, and θ, which captures the sensitivity of the buy (resp. sell) liquidity demand to prices. Specifically, increasing (resp. lowering) the ask (resp. bid) $1/\kappa$ by s reduces demand by $N\,\theta\,s/2$, which, when normalised by aggregate demand, is $\theta\,s$. Liquidity demand in our model is similar to the reduced form demand functions in the models of Garman (1976); Ho and Stoll (1981); Hendershott and Menkveld (2014). The parameter θ can also be interpreted as capturing the competitiveness and fragmentation of the market. As the market becomes more competitive and the value of θ increases, the likelihood that liquidity traders avoid transacting in the AMM because cheaper alternatives are available increases. Finally, the liquidity supplier's fee revenue, given by the cumulative fees from buyers and sellers, is

$$\pi\,N\ (1 - \theta/\kappa)\ . \tag{7}$$

The liquidity supplier does not hold the same information about the future liquidation value V of the security as that of informed traders. At stage one, he assumes that with probability $1/2$, the liquidation value V of the security is positive, in which case the informed traders buy the security and their private signals are drawn from the interval $[0, \overline{v}]$ according to a continuous and differentiable density f, and with probability $1/2$, the liquidation value of the asset is negative, in which case the informed traders sell the security and both their signals are drawn from the interval $[-\overline{v}, 0]$, according to the density $f(-x)$.

Let δ denote the total trading volume of informed traders. From the perspective of the supplier, δ is a random variable, whose expected value is zero, and which we assume to be independent of the uninformed liquidity demand. Let $\mathbb{E}_{\mathrm{L}}$ denote the expectation operator conditional on the liquidity supplier's information at stage one. The liquidity supplier balances fee revenue with expected losses to informed traders. These losses are defined in (6) as

$$-\frac{1}{\kappa}\,\mathbb{E}_{\mathrm{L}}\left[\delta^2\right] = -\frac{1}{\kappa}\,\mathbb{V}_{\mathrm{L}}[\delta]\,, \tag{8}$$

which increase with the variance of the informed trading volume.

As shown below, the variance of the informed traders' volumes increases with that of their private signals. Moreover, the variance of informed signals is closely tied to blockchain slot length, i.e., block time. As block time increases, the likelihood of extreme changes in the fundamental value of the risky security rises, and longer block times allow traders more opportunities to observe signals and gather information, including from competing exchanges. In the remainder of this paper, we assume that the variance of signals increases with block time.

***Stage 2*: liquidity taking.** Throughout the blockchain slot, informed and uninformed liquidity traders submit transactions to the memory pool. Two risk-neutral informed traders, i and j, compete for queue priority in the next block. As detailed in Appendix A, PGAs among informed traders are online auctions with a hard close corresponding to the end of the blockchain slot, during which traders can only revise their priority fee bids $\{\varphi_i, \varphi_j\}$ upward (similar to an English auction); see Appendix A for details on the mechanisms of priority fee bidding in Ethereum.

A key implication of pre-trade transparency in memory pools is that traders observe pending transactions. This allows them to sequentially raise their bids throughout the PGA to compete for queue priority. Just before block creation, traders have a final opportunity to revise upward their priority fees simultaneously. Competition at this round is a first-price sealed-bid auction with a reserve price equal to the highest bid submitted thus far. In the perfect Bayesian equilibrium, traders determine both their priority fees $\{\varphi_i, \varphi_j\}$ and trading volumes $\{\delta_i, \delta_j\}$. The auction of the final round is blind because traders submit transactions immediately before the end of the slot, and it is first-price rather than all-pay, since traders use price limits in their strategies.[5]

[5]Specifically, each trader submits two transactions to the memory pool: one with the equilibrium priority fee and a price limit set to $V_0 + \delta/\kappa$, and another with an ϵ-priority-fee and no price limit. If a trader loses the auction, the transaction with the price limit is not executed, while the ϵ-priority-fee transaction is. Conversely, if the trader wins

An informed trader looking to buy the risky security may find it more profitable to avoid competition for priority in a PGA if sell orders from uninformed traders with better queue position improve her execution price. However, our model assumes that transactions with zero priority fees are placed randomly within the block, and on average, an equal number of buy and sell orders for uninformed liquidity demanders would be executed before and after the informed trader's transaction. Thus, the execution outcome is comparable to losing the auction and being placed second in the block. As a result, in expectation, losing the auction is never profitable and informed traders find it more profitable to compete for queue priority.

At the start of the PGA, traders observe their private signals $\{v_i, v_j\}$ about the liquidation value V simultaneously and they know each other's type, i.e., whether they are both buyers or both sellers. In our model, V is a statistic of both signals, and we write the expected liquidation value from the perspective of trader i as

$$V_i = \mathbb{E}_i \left[V \mid v_i \right] = \int \mathbb{E} \left[V \mid v_i, v_j = x \right] \, f\left(x\right) \, dx \, . \tag{9}$$

In what follows, we make the following assumption

ASSUMPTION 1: *The expected liquidation value V_i in* (9) *is an increasing function of v_i.*

Assumption 1 reflects the intuitive relationship between higher private signals and higher estimates of the liquidation value.

At the end of the PGA, a block is created with the informed and the uninformed liquidity traders' transactions. The final value V of the asset is then realised and all randomness is resolved.

III. Price formation, priority fees, and trading volumes

This section studies the priority fee bidding strategy of traders who compete for execution when the liquidity depth in the AMM is κ. Recall that $\{\varphi_i, \varphi_j\}$ denote the priority fees and $\{\delta_i, \delta_j\}$ denote the trading volumes. Assume that both traders know that the liquidation value V is positive, so they wish to buy the risky security. The case where both traders are sellers is symmetric and leads to the same equilibrium priority fees and trading volumes.

A. Price formation

PROPOSITION 1: *The strictly dominant strategy for informed traders is late bidding, i.e., submitting priority fees immediately before the end of the blockchain slot.*

The result shows that each informed trader finds it optimal to delay bidding until the last moment because any non-zero bid before the end of the blockchain slot acts as a reservation price for the final auction. Proposition 1 also shows that private information is only revealed immediately

the auction, only the transaction with the price limit is executed.

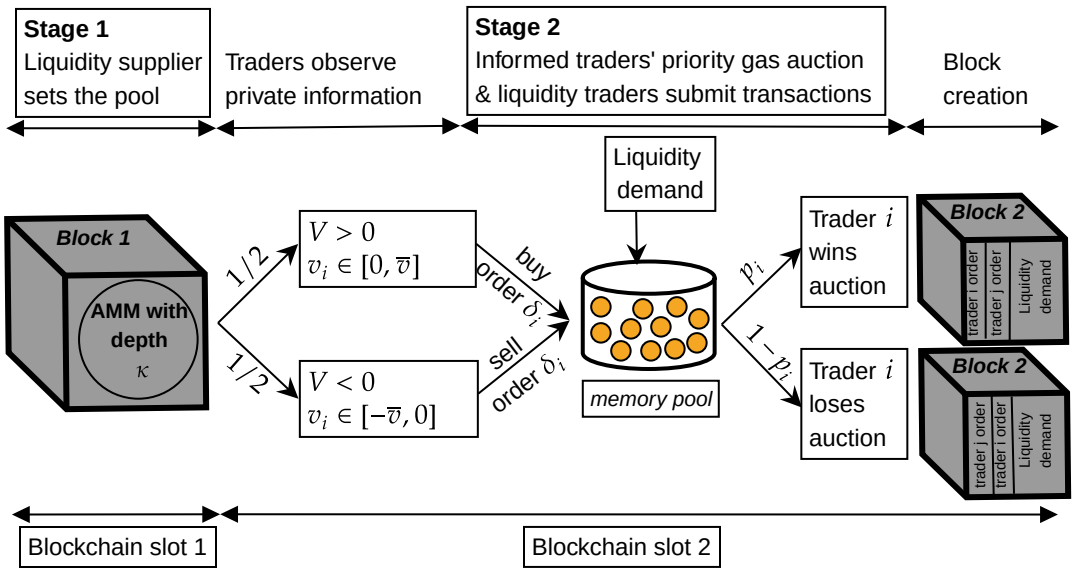
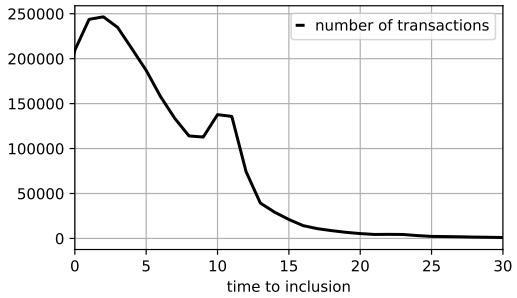
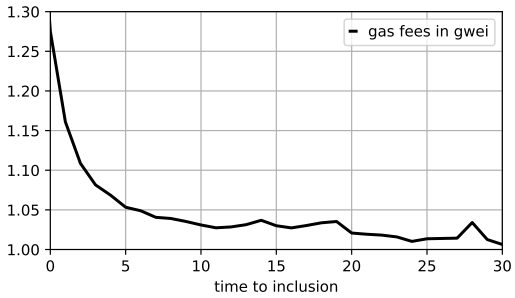


Figure 2. Sequence of events.

before the creation of the next block. In practice, this implies that information is disseminated to the market with the same periodicity as that of the creation of blocks, which in Ethereum occurs every 12 seconds. This pattern is observed in practice: transactions with large priority fees, typically associated with informed trading as shown in Capponi, Jia, and Yu (2023b), are predominantly submitted to the memory pool shortly before the end of each blockchain slot; see Figures 3a and 3b.



(a) Distribution of the average number of transactions as a function of the time (in seconds) between submission to the mempool and inclusion in a block.



(b) Distribution of the average priority fee of transactions as a function of the time (in seconds) between submission to the mempool and inclusion in a block.

Figure 3. Priority fees timing and magnitude from Ethereum transaction data between 10 and 16 December 2022.

This feature of the microstructure of DEXs has implications for price efficiency, defined here as the variance of the liquidation value V conditionally on all public information. In traditional electronic exchanges, information can be hidden in orders sent at the frequency of liquidity demand

flow so the conditional variance of V either decreases at a constant rate, or decreases steeply relatively early in trading games; see Kyle (1985b); Holden and Subrahmanyam (1992); Foster and Viswanathan (1996); Huddart et al. (2001). In contrast, a vehicle for price discovery in blockchains is priority fees, and price discovery in blockchains is a step process where information is only revealed periodically and immediately before each block is created.

This property, on its own, cannot be deemed inherently beneficial or detrimental to decentralised markets. However, if there is a competing trading venue with continuous price formation that is a reliable source of information for speculation in the DEX (e.g., Binance), then the variance of signals at the end of each slot rises, and so does the variance of the corresponding trading volumes, leading to liquidity shortages in the DEX, as we show below. More critically, price discovery would shift to the competing venue, because liquidity suppliers are drawn to the less risky alternative.

The study of agent behaviour throughout slots in DEXs operating on blockchains resembles the study of agent behaviour during preopening sessions of traditional electronic exchanges. In both settings, markets are not cleared until some given time. At the end of preopening sessions, all orders are executed at a clearing price that maximises trading volume. In contrast, orders in the memory pool are sequenced and executed based on their priority fees. While there are fundamental differences in the purpose and mechanics of preopening sessions and blockchain slots, similarities exist. Like memory pools, preopening sessions do not clear markets, but agents can communicate with one another. However, unlike memory pools, agents in preopening sessions of traditional electronic markets observe only partial information about the market state, such as liquidity supply at the best prices or a virtual clearing price; see Van Bommel and Hoffmann (2011) for further details. Biais et al. (1999) propose several hypotheses regarding the informativeness of preopening prices. Our findings in Proposition 1 support the *pure-noise hypothesis*, which posits that trading activity before the end of the slot contains no new information and that strategies may hinder price discovery. Similarly, Medrano and Vives (2001) find that trading volumes and information revelation accelerate toward the end of preopening sessions, providing further empirical support for our results.

B. Priority fees

Proposition 1 shows that it is more profitable for traders to submit their transactions at the end of block time. Thus, the PGA reduces to a first-price sealed-bid auction in which traders set both their priority fees and trading volumes. This section studies the Bayesian-Nash equilibrium priority fees. The game is symmetric and we assume that both traders' equilibrium strategies consist of both a priority fee and a trading volume. The game is symmetric, so we describe the game from the perspective of trader i.

In what follows, we assume for simplicity that trader i approximates the impact of her competitor's trade on the marginal price based on her own private signal v_i.[6] We characterise the

[6]This assumption is further justified by δ_i and δ_j being small relative to the total liquidity supply, so they can be treated as equal to a first-order approximation.

equilibrium priority fees, trading volumes, and liquidity in Appendix C without this approximation and show that all results hold, though with more complex expressions.

If trader i wins the auction, i.e., if $\varphi_i > \varphi_j$, her buy order is executed first, so the execution price for her trade is $V_0 - \delta_i/\kappa = -\delta_i/\kappa$; see (2). Thus, the trader's terminal wealth in this case is

$$W_i\,(\text{win}) = -\,\varphi_i - \underbrace{\delta_i\;(\delta_i/\kappa + \pi)}_{\text{initial trade}} \quad + \quad \underbrace{\delta_i\,V}_{\text{inventory value}} \quad .$$

However, if trader j's order is executed first, i.e., if $\varphi_i < \varphi_j$, then the execution price for trader i's order is $3\,\delta_i/\kappa$ instead; see (3). Thus, her wealth is

$$W_i\,(\text{lose}) = -\,\underbrace{\delta_i\;(3\,\delta_i/\kappa + \pi)}_{\text{initial trade}} \quad + \quad \underbrace{\delta_i\,V}_{\text{inventory value}} \quad .$$

When submitting a transaction, trader i determines both the priority fee and the trading volume. At this stage, trader i knows the liquidity depth κ and recognises that queue priority is secured if her priority fee φ_i is greater than that of her competitor. While trader i does not observe the competitor's priority fee directly, she can compute the probability that her fee is higher. Denote this probability by p_i. Before the end of the slot and the creation of the block, the expected utility of the risk-neutral trader is

$$\begin{aligned}\mathbb{E}_i\,[W_i] &= -\,3\,\delta_i^2/\kappa + \delta_i\;(V_i - \pi) + p_i\;\left(-\varphi_i + 2\,\delta_i^2/\kappa\right) &(10)\\ &= \mathbb{E}_i[W_i(\text{lose})] + p_i\;\left(-\varphi_i + 2\,\delta_i^2/\kappa\right)\,, &(11)\end{aligned}$$

where $p_i = \mathbb{P}_i\,[\varphi_i > \varphi_j]$, so trader i solves the problem

$$\sup_{\delta_i}\,\sup_{\varphi_i}\,\mathbb{E}_i\,[W_i] = \sup_{\delta_i}\,\sup_{\varphi_i}\,\left\{p_i\;\left(-\varphi_i + 2\,\delta_i^2/\kappa\right) - 3\,\delta_i^2/\kappa + \delta_i\;(V_i - \pi)\right\}\,. \tag{12}$$

For simplicity, we assume that the expected liquidation value V_i, conditional on knowing that $V > 0$, is larger than π. The objective function in (12) is a bounded real-valued function, allowing the interchange of the order in which one computes the suprema with respect to δ_i and φ_i.[7]

The expected wealth in (11) can be interpreted as follows. When trader i loses the PGA, her expected wealth is $\mathbb{E}_i[W_i(\text{lose})]$. However, if she submits a priority fee φ_i, then with probability p_i she gains a surplus from queue priority. This surplus arises from the difference between the *reservation priority fee* $2\,\delta_i^2/\kappa$, and the actual priority fee φ_i submitted by the trader in the memory pool. The reservation priority fee $2\,\delta_i^2/\kappa$ represents the fee at which trader i is indifferent between winning or losing the PGA. It corresponds to the price impact that the trader avoids when she secures queue priority in the block.

Intuitively, traders buy and sell volumes proportional to their private signals. In the optimi-

[7] In the symmetric case, when informed traders are sellers, we assume that the expected liquidation value V_i, conditional on knowing that $V < 0$, is smaller than $-\pi$.

sation problem (12), the trading volume δ_i for trader i depends on V_i, which, as defined in (9), is itself a function of only the trader's private signal v_i. Similarly, the priority fee φ_i depends on the trading volume δ_i. Thus, in equilibrium, both the volume δ_i and the priority fee φ_i are functions of the private signal v_i.[8]

Recall that this section describes the game when both traders buy the security (the analysis is identical when they sell). Let $\delta_i = \delta(v_i)$ denote the random variable describing the volume transacted by trader i. By assumption, the trading volume is drawn from the interval $[\underline{\delta}, \overline{\delta}]$ according to the density function

$$g(x) = f\left(\delta^{-1}(x)\right) \Big/ \delta'\left(\delta^{-1}(x)\right). \tag{13}$$

Consequently, from the optimisation problem (12), trader i solves

$$\sup_{\varphi_i} \left\{ p_i \left(-\varphi_i + 2\,\delta_i^2/\kappa \right) \right\} \tag{14}$$

to obtain her optimal priority fee $\varphi_i^\star = \varphi(\delta_i)$ for a trading volume δ_i. That is, the trader sets her priority fee to maximise the product of the probability to win the auction and the surplus earned from queue priority. Trader i faces a tradeoff, decreasing the priority fee increases the profit per unit bought but it reduces the probability to obtain queue priority. This tradeoff is akin to a monopolist who faces a demand curve, or to a dealer who sets bid and ask quotes; see Biais (1993). The problem (14) is equivalent to a first-price sealed bid private value auction in which the item's value is $2\,\delta_i^2/\kappa$. Here, the object of competition is the adverse price impact that the informed trader avoids by winning the PGA.

When solving for the equilibrium at stage two, informed traders take the depth κ—determined at stage one—as fixed and independent of the priority fee φ_i. In other words, the priority fee does not directly influence the liquidity depth but has an indirect effect. As shown in the next section, the liquidity supplier accounts for the priority fee and the resulting trading volumes to determine the depth of the AMM's pool.

Trader i expects trader j to employ the increasing priority fee bid strategy $\varphi(\cdot)$. Therefore, the probability of obtaining queue priority in the block is

$$p_i = \mathbb{P}_i\left[\varphi_i > \varphi_j\right] = \mathbb{P}_i\left[\varphi^{-1}(\varphi_i) > \delta_j\right] = G\left(\varphi^{-1}(\varphi_i)\right),$$

where G is the cumulative distribution function corresponding to the density g of δ_j. Consequently, the first-order condition derived from the optimisation problem in (14) is

$$\frac{1}{\varphi'\left(\varphi^{-1}(\varphi_i)\right)}\, g\left(\varphi^{-1}(\varphi_i)\right) \times \left(-\varphi_i + \frac{2\,\delta_i^2}{\kappa} \right) - G\left(\varphi^{-1}(\varphi_i)\right) = 0\,.$$

In a Bayesian-Nash equilibrium, trader i finds it optimal to adopt the same strategy φ, which pins

[8] Specifically, note that $\partial_{\delta_i}\mathbb{E}_i[W_i]$ is a function of V_i which is itself a function of only the signal v_i, i.e., $\partial_{\delta_i v_i}\mathbb{E}_i[W_i] \neq 0$. Thus, the optimal trading volume $\arg\max_{\delta_i}\mathbb{E}_i[W_i]$ is a function of the signal v_i. Similarly, $\partial_{\varphi_i v_i}\mathbb{E}_i[W_i] \neq 0$, so the priority fee also depends on the signal value.

down the equilibrium strategy. The solution is characterised in the following result.

PROPOSITION 2: *The equilibrium priority fee is*

$$\varphi_i^\star = \frac{2}{\kappa}\left(\delta_i^2 - 2\,\frac{\int_{\underline{\delta}}^{\delta_i} x\,G\left(x\right)dx}{G\left(\delta_i\right)}\right). \tag{15}$$

The priority fee is increasing in the trading volume.

When computing her optimal priority fee, trader i uses the reservation priority fee $2\,\delta_i^2/\kappa$ as a baseline. This fee represents the priority fee level at which she is indifferent between winning or losing queue priority. Trader i has an incentive to lower her priority fee to capture a surplus. This is reflected in (15), which shows that trader i applies a discount $2\int_{\underline{\delta}}^{\delta_i} x\,G\left(x\right)dx/G\left(\delta_i\right)$ to the reservation priority fee. More precisely, as the value of trader i's private signal v_i increases, the probability that her reservation priority fee exceeds that of trader j also rises. This makes it more likely that she secures queue priority and reduces the need to compete by further raising the priority fee. As a result, trader i applies a larger discount to the reservation priority fee as the value of her private signal increases. Finally, when liquidity supply is abundant, competition diminishes as the cost of losing queue priority becomes less significant.

C. Trading volumes

Next, substitute the optimal priority fee $\varphi_i^\star$ in (15) into the objective function (12)to write the optimisation problem

$$\begin{aligned}&\sup_{\delta_i}\left\{G\left(\delta_i\right)\,\left(-\varphi_i^\star + 2\,\delta_i^2/\kappa\right) - 3\,\delta_i^2/\kappa^2 + \delta_i\,\left(V_i - \pi\right)\right\}\\ =&\sup_{\delta_i}\left\{F\left(v_i\right)\,\left(-\varphi_i^\star + 2\,\delta_i^2/\kappa\right) - 3\,\delta_i^2/\kappa^2 + \delta_i\,\left(V_i - \pi\right)\right\}\end{aligned} \tag{16}$$

to obtain trader i's optimal trading volume.

In what follows, we make the following assumption for simplicity.

ASSUMPTION 2: *We assume that $V_i > \pi$ for all $v_i \in [0, \overline{v}]$ when informed traders are buyers and that $-V_i > \pi$ for all $v_i \in [-\overline{v}, 0]$ when informed traders are sellers.*

Assumption 2 ensures that informed traders always execute trades that are expected to be profitable, even after accounting for the transaction fee $\pi\,\delta_i$.

The linear-quadratic program (16) can be interpreted as follows. In equilibrium, both traders employ the same priority fee bidding strategy, allowing them to estimate, on average, the priority fee costs $\varphi_i^\star$ they incur on the blockchain when observing a trading signal v_i. Additional trading costs incurred by trader i in the AMM include (i) the execution cost $-\delta_i^2/\kappa$, (ii) the price impact cost $2\,\delta_i^2\left(1 - F\left(v_i\right)\right)/\kappa$, which decreases with the probability $F\left(v_i\right)$ of winning the PGA, and (iii)

the AMM's proportional transaction fee $\pi\,\delta_i$. Both trading and infrastructure costs increase with trading volume, creating an incentive for trader i to reduce her trading volume δ_i. However, at the end of the slot, when the liquidation value of the asset is realised, trader i holds δ_i units of the risky security, whose expected value is positive. This provides an incentive for trader i to increase her holdings δ_i in the risky security. The next result characterises this tradeoff in equilibrium.

PROPOSITION 3: *The equilibrium trading volume is*

$$\delta_i^\star = \kappa\,\tilde{\delta}_i = \kappa\,\frac{V_i - \pi}{2\,(3 - 2\,F\,(v_i))}\,, \tag{17}$$

and it is an increasing and continuously differentiable function of the private signal.

In equilibrium, trader i's volume δ_i is linear in the liquidity depth κ, so the trader transacts a *fraction* $\tilde{\delta}_i$ of the pool's liquidity supply. This fraction depends on the observed private signal and the distribution of the competitor's trading signal as follows. The fraction $\tilde{\delta}_i$ increases with the private signal for two reasons. First, as the signal increases, the expected liquidation value V_i also rises, creating an incentive to trade more because the transaction becomes more profitable. Second, as the value of the signal increases, the likelihood of securing priority in the block at a cost lower than the reservation priority fee $2\,\delta_i^2/\kappa$ increases, encouraging higher trading volumes.

The fraction $\tilde{\delta}_i$ of the pool transacted by trader i also depends on the distribution f of her competitor's signal. For a fixed private signal v_i, this distribution plays two roles. First, as the range of possible signal values $[0, \overline{v}]$ widens, V_i in (9) increases due to the higher expected value of the competitor's signal, creating an incentive to trade more. However, a wider range also increases the probability $1 - F(v_i)$ that trader i's signal is lower than that of her competitor, increasing the likelihood of losing the auction. This introduces potential costs, which in turn reduces trading volumes. We explore these opposing effects in more detail below in Section **??**.

One key implication of Proposition 3 is that the impact of trader i's order on the marginal price of the AMM, defined in (3), is

$$2\,\delta_i^\star/\kappa = 2\,\tilde{\delta}_i\,.$$

The impact does not depend on the level of liquidity supply κ but instead depends solely on the distribution of trading signals and the competition for queue priority. Specifically, in the absence of PGAs, both traders transact a fraction

$$\tilde{\delta}_i = \frac{V_i - \pi}{4}\,,$$

so the average impact of their trading activity on the marginal price is

$$\mathbb{E}[V_i - \pi]\,.$$

Thus, the difference between AMM prices in this case and the price implied by all private information is the AMM's fee rate. When there are PGAs, the fraction $\tilde{\delta}_i$ transacted by each trader

decreases, and this decrease is more pronounced when signal distribution is heavy-tailed, or equivalently when block time is long. Consequently, PGAs and block time increase the difference between the marginal price and the price implied by all private information, reducing the informational content of prices.

Proposition 3 also characterizes the distribution of trading volumes within each block. Higher values of private signals correspond to larger trading volumes, and as shown in Proposition 2, they are also associated with higher priority fees and better queue positions. Figure 4 illustrates the average absolute trading volume of transactions across multiple Uniswap v3 pools as a function of their queue position within the block. The figure shows that transactions executed first in the block tend to have larger average trading volumes than those behind in the queue. This pattern lends empirical support to the findings of our model, where trading volumes increase with trading signals and better queue positions.

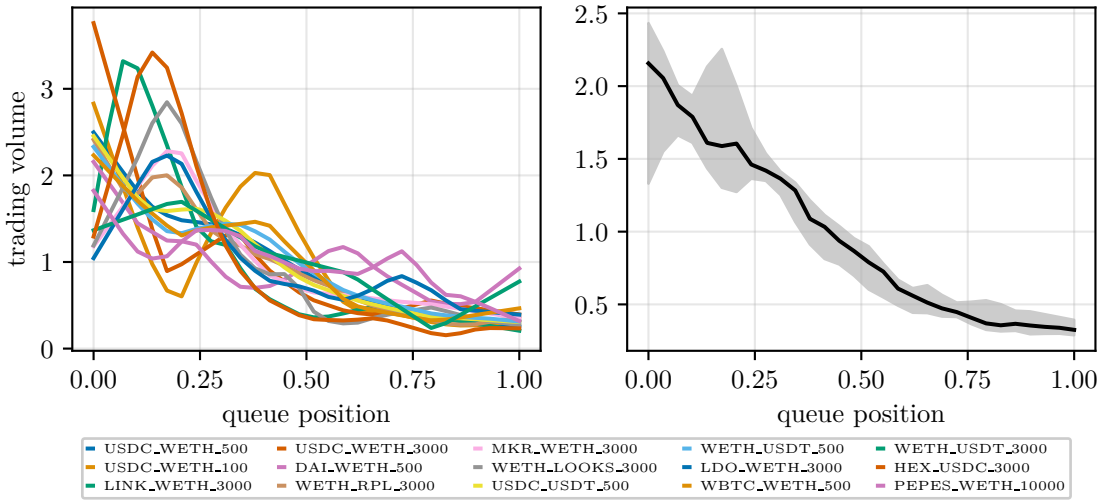


Figure 4. Left panel: Average absolute trading volume as a function of queue position in the block for transactions in multiple Uniswap v3 pools; 0 corresponds to first position and 1 to last position. The transactions are between 1 January 2023 and 31 December 2023 in 15 different Uniswap V3 pools with multiple transactions in at least 10 different blocks. For each pool, the trading volumes are normalised by the standard deviation of trading volumes. Right panel: average and interquartile trading volumes across the 15 pools.

Finally, similar arguments as those in Sections III.B and III.C show that the equilibrium priority fees and trading volumes derived earlier also apply when traders wish to sell the security ($V < 0$). The results require only a slight adjustment: replace v_i with $-v_i$ and V_i with $-V_i$. As a consequence, traders are symmetrically aggressive in equilibrium, i.e., they buy or sell the same volumes for signals of equal absolute value and opposite signs.

IV. Equilibrium liquidity supply

This section examines liquidity supply in stage one. We assume that a risk-neutral liquidity supplier provides liquidity during this stage, submitting a transaction in the block immediately before the one in which traders compete for execution priority.

As described in Section II.B, the liquidity supplier balances adverse selection losses to informed traders with fee revenue from uninformed liquidity traders. However, he does not know wether the security's value will increase or decrease, and assigns a 50% probability to each case. Use (8) and (17) to write the expected loss to informed traders as

$$-\mathbb{V}_{\mathrm{L}}\left[\delta_i\right]/\kappa - \mathbb{V}_{\mathrm{L}}\left[\delta_j\right]/\kappa = -2\,\mathbb{V}_{\mathrm{L}}\left[\delta_i\right]/\kappa = -2\,\kappa\,\mathbb{V}_{\mathrm{L}}[\tilde{\delta}_i]\,. \tag{18}$$

In Section II.B, we argue that for a fixed trading volume, higher liquidity supply reduces losses to informed traders by limiting price impact. In contrast to these observations, in the equilibrium of our game, trading volume of informed traders is not fixed but it is a function of liquidity supply. Thus, when computing his expected losses, the supplier anticipates that informed traders transact volumes that are proportional to the liquidity supply, and that providing more liquidity amplifies, on average, the dollar value of the speculative profits of traders.

The liquidity supplier balances losses to informed traders with fees earned from trading with uninformed liquidity traders. As previously detailed, the net volume of this trading activity is zero, while the absolute volume is elastic and its maximum equals N. Specifically, this consists of $(1-\theta/\kappa)\,N/2$ in buying quantity and $(1-\theta/\kappa)\,N/2$ in selling quantity, where θ represents the price elasticity of liquidity demand. The optimisation problem of the liquidity supplier, which is solved in the next proposition, is

$$\sup_{\kappa}\left\{\pi\,N\,\left(1-\theta/\kappa\right) - 2\,\kappa\,\mathbb{V}_{\mathrm{L}}[\tilde{\delta}_i]\right\}\,. \tag{19}$$

PROPOSITION 4: *In equilibrium, the liquidity supply is*

$$\kappa^{\star} = \sqrt{\frac{\pi\,N\,\theta}{2\,\mathbb{V}_L[\tilde{\delta}_i]}}\,, \tag{20}$$

where $\delta_i^{\star}$ is defined in (17)*, and the liquidity supplier's expected payoff is*

$$\pi\,N - 2\,\sqrt{2\,\pi\,N\,\theta\,\mathbb{V}_L[\tilde{\delta}_i]}\,. \tag{21}$$

The liquidity supply increases with the profitability of liquidity demand: it rises with the fee rate π, and with the demand volume N and its inelasticity. Additionally, the liquidity supplier anticipates that informed traders will transact the fraction (17) of the pool, which determines his own losses. Consequently, he reduces liquidity supply when the variance of this fraction increases. From the supplier's perspective—who does not observe private signals—this variance depends solely

on the distribution of informed traders' private signals. Specifically, the more volatile the signals, the lower the liquidity supply.

In practice, Ethereum blockchains operate with slots lasting 12 seconds. The time length of the slot has two opposing effects. One, informed traders submit transactions at the end of the slot, which can lead to highly profitable and/or volatile trading signals when considered from the perspective of liquidity suppliers, particularly for risky cryptocurrencies or when competing venues with continuous price discovery coexist with the DEX. These effects drive liquidity levels down. Two, when slots are long, liquidity demand accumulates, so the demand volume N increases. This effect drives liquidity levels up.

As detailed in the next section, PGAs in memory pools reduce the negative effect of signal variance on liquidity supply. PGAs reduce the fraction $\tilde{\delta}$ of the pool transacted by informed traders. This mechanism transfers part of the revenue from informed traders to validators, who ensure the blockchain's security. The resulting reduction in trading volumes leads to increased liquidity and lower trading costs for uninformed liquidity traders.

The equilibrium liquidity depth (20) and the supplier's payoff in (21) establish the condition

$$\frac{\pi\, N}{8\,\theta} \geq \mathbb{V}_{\mathrm{L}}[\tilde{\delta}_i] \tag{22}$$

for the viability of liquidity provision in AMMs. Condition (22) is standard, it states that if the fee revenue from liquidity demand is less than the expected losses to informed traders, the supplier's profits become negative, making liquidity provision unsustainable. The degree to which this condition must hold depends on the price elasticity θ. All else being equal, as demand becomes more elastic, the viability of liquidity provision requires either greater liquidity demand N, higher fee rates π, or reduced variance in trading volumes. This condition mirrors that in Glosten and Milgrom (1985) where markets shutdown if the signal of informed traders is too precise relative to the elasticity of liquidity demand.

When the variance is maximal, i.e., when

$$\mathbb{V}_{\mathrm{L}}[\tilde{\delta}_i] = \frac{\pi\, N}{8\,\theta}\,, \tag{23}$$

then the minimal liquidity depth, for which the supplier breaks even, is

$$\underline{\kappa}^{\star} = 2\,\theta\,. \tag{24}$$

As demand becomes more elastic, the necessary supply to break even also rises.

Finally, in practice, not all liquidity suppliers are *rational*. Unlike traditional trading venues such as high-frequency limit order books or dealer markets, the permissionless nature of blockchains facilitates entry to provide liquidity, particularly by less sophisticated liquidity suppliers. As a result, strategic liquidity suppliers in AMMs cannot freely set the price of liquidity because they compete with *noise liquidity suppliers*. Let the liquidity already provided by noise liquidity suppliers

in the AMM be denoted by κ'. In this context, the strategic liquidity supplier faces the decision of either adding liquidity to reach the target supply $\kappa^\star$ in (20) when $\kappa^\star > \kappa'$, or refraining from further liquidity provision if the existing supply already exceeds $\kappa^\star$. This feature of DEXs may explain the losses observed in practice in current AMMs; see Cartea et al. (2024a).

V. Price efficiency

To analyse price efficiency in DEXs, we extend the model in Sections III and IV to incorporate additional strategic considerations. Specifically, we introduce costly information gathering and allow informed traders to act as blockchain validators.

A. Priority fees, trading volumes, and liquidity supply

Assume there are M traders competing for block priority, each paying a fixed cost C to acquire private information. These costs include expenses for proprietary blockchain data, centralised exchange data, searcher contract deployment, and blockchain monitoring tools. More importantly, they include the monetary and computational costs of operating a blockchain node. Running a node facilitates participation in blockchain validation, so we assume that once the cost C is incurred, the trader also participates in blockchain validation. Let R denote the validation reward issued by the blockchain to the block validator,[9] assumed to be randomly selected from all blockchain nodes. We further assume that the M informed traders represent a fraction β of all blockchain validators, so each informed trader has a probability β/M of being selected by the blockchain's protocol.[10]

We extend our model by introducing an initial stage where traders decide whether to pay the cost C to acquire private information and participate in blockchain validation. Let L be the total number of traders eligible to acquire information, and let $M \leq L$ be the subset that chooses to do so. As in the previous game, the liquidity supplier sets the AMM's depth κ in stage one, based on rational expectations of the trading volumes of informed traders. In stage two, informed traders observe their private signals and compete for queue priority. The game is solved by backward induction and is illustrated in Appendix D.

Similar to the previous sections, we focus on the case where all traders are buyers. In the final stage (stage two), trader i competes in the PGA against $M-1$ other informed traders. If trader i wins, her buy order is executed first at the price $-\delta_i/\kappa$, and her resulting wealth is

$$W_i\left(\text{win}\right) = -\varphi_i - \underbrace{\delta_i\,\left(\delta_i/\kappa + \pi\right)}_{\text{initial trade}} \quad + \underbrace{\delta_i V}_{\text{inventory}} \quad - \underbrace{C}_{\text{cost}} + \underbrace{\frac{\beta}{M}\,\varphi_i + \frac{\beta}{M}\,R}_{\text{validation reward}}. \tag{25}$$

If trader i loses, then we assume that her order is placed randomly among the $M-1$ orders

[9] In Proof-of-Stake blockchains like Ethereum, validation requires staking ETH, which introduces an opportunity cost. We denote the net validation reward, after accounting for this cost, by R, and assume it remains positive our mode.

[10] In Ethereum, this implies that each trader *stakes* the same amount of ETH.

corresponding to the $M-1$ losing bids. Her execution price is $-(1+M)\,\delta_i/\kappa$ instead, and her resulting wealth is

$$W_i\,(\text{lose}) = -\underbrace{\delta_i\,\left((1+M)\,\delta_i/\kappa+\pi\right)}_{\text{initial trade}} \;+\; \underbrace{\delta_i\,V}_{\text{inventory}} \;-\; \underbrace{C}_{\text{cost}} + \underbrace{\frac{\beta}{M}\,\max\left\{\varphi_{-i}\right\}+\frac{\beta}{M}\,R}_{\text{validation reward}}. \tag{26}$$

where φ_{-i} denotes the bids of all other traders. Thus, the expected wealth of trader i is

$$\begin{aligned}\mathbb{E}_i\left[W_i\right] =& p_i\left(-\left(1-\frac{\beta}{M}\right)\varphi_i + M\,\delta_i^2/\kappa\right)\\ &-\delta_i\,\left((1+M)\,\delta_i/\kappa+\pi\right)+\delta_i\,V_i - C+\frac{\beta}{M}\,\left(R+\mathbb{E}\left[\varphi_{(M)}\mid\varphi_{(M)}>\varphi_i\right]\right),\end{aligned}$$

where $p_i=\mathbb{E}_i[\varphi_i>\varphi_{-i}]$, $\varphi_{(M)}$ denotes the (random) largest priority fee, and $\mathbb{E}\left[\varphi_{(M)}\mid\varphi_{(M)}>\varphi_i\right]$ denotes its expectation conditional on losing the auction. The term β/M is the probability that an informed trader is selected as the block validator. Note that priority fees incentivise blockchain validation, enhancing its security. The following result characterises the equilibrium priority fees, trading volumes, and liquidity supply of stage two and stage one. We omit the proofs because they follow arguments similar to those in Propositions 2 and 3.[11]

PROPOSITION 5: *The equilibrium priority fee of stage two is*

$$\varphi\left(\delta_i\right)=\frac{M}{\kappa\left(1-\frac{\beta}{M}\right)}\left(\delta_i^2-2\,\frac{\int_{\underline{\delta}}^{\delta_i}x\,G\left(x\right)^{M-1}\,dx}{G\left(\delta_i\right)^{M-1}}\right), \tag{27}$$

which is increasing in the trading signal. For a fixed trading volume δ, the priority fee increases in the number of informed traders M. The equilibrium trading volume in stage two is

$$\delta(v_i)=\kappa\,\tilde{\delta}(v_i)=\kappa\,\frac{V_i-\pi}{2\left(1+M\left(1-F\left(v_i\right)^{M-1}\right)\right)} \tag{28}$$

which increases in the trading signal and decreases to zero with the number of informed traders. In particular, the equilibrium priority fee $\varphi(\delta(v_i))$ decreases to zero in the number of informed traders M. Finally, the liquidity depth in stage one is

$$\kappa^{\star}=\sqrt{\frac{\pi\,N\,\theta}{M\,\mathbb{V}_L[\tilde{\delta}_i]}}. \tag{29}$$

The liquidity supply increases with the number of informed traders M.

For a fixed trading volume δ, as the number of informed traders increases, the adverse price impact $M\,\delta/\kappa$ also increases, forcing each trader to increase their priority fees $\varphi(\delta)$. However,

[11] See also Biais (1993) for related derivations in the context of traditional markets, where entry into the market-making business incurs costs.

trading volume is part of the informed trader's equilibrium strategy and it adjusts to trading costs, including execution costs and priority fees. In equilibrium, the trading volume $\delta(v)$ in (28) decreases as the number of informed traders increases in anticipation of higher expected priority fees. Consequently, the equilibrium priority fees $\varphi(\delta(v))$, accounting for strategically adjusted trading volumes, decrease with the number of informed traders in the memory pool. In the limit, as M approaches infinity, trading volumes and priority fees converge to zero, and liquidity supply grows unbounded to attract the totality of the elastic uninformed liquidity demand.

B. Price efficiency in DEXs

In this section, we analyse price efficiency defined as the variance of the future security's liquidation value V conditional on all public information, from the perspective of an uninformed individual. Specifically, we analyse the number of informed traders who pay the cost of acquiring information, as this is directly related to price efficiency. Our analysis shares a similar goal with that in Grossman and Stiglitz (1980) for traditional markets, where the degree of market informativeness and efficiency depends on the information held by informed traders, and their number is endogenously determined.

More precisely, in blockchains, private information is revealed through the fully revealing priority fee (27) if the trader wins the PGA or through the traded volume (28) if the trader loses the PGA. Let L denote the number of traders who decide whether or not to pay the cost of information C at stage zero.[12] In our analysis, we assume that each private signal reduces the variance of the security's liquidation value V conditional on all public information. To illustrate this, consider the following example. Assume that the statistic V is the average of the L signals, i.e.,

$$V = \frac{1}{L}\sum_{k=1}^{L} v_i + \epsilon\,,$$

where ϵ is unobservable noise with variance ξ^2, and let σ^2 denote the variance of each signal v_i. In equilibrium, a subset $M \leq L$ of traders pay the information cost C, so the variance of the liquidation value V conditional on public information can be expressed as

$$\mathbb{V}[V \mid \{v_1, \ldots, v_M\}] = \frac{L-M}{L^2}\sigma^2 + \xi^2.$$

Clearly, price efficiency improves as more traders pay the cost of information.

In equilibrium, the number of traders who choose to become informed is constrained by the relative profitability of informed trading and the cost C. At stage zero, the equilibrium number of traders M engaging in informed trading is determined such that the marginal utility gain from switching between informed and uninformed trading is negative. We characterize the equilibrium number of informed traders in the following result.

[12] In blockchains, the number of transactions, and thus the number of informed traders, is limited by the finite size of each block.

PROPOSITION 6: *The equilibrium number of informed traders is the integer part of the solution to*

$$C = H(M) = \underbrace{\sqrt{\frac{\pi\, N\, \theta}{M\, \mathbb{V}_L[\tilde{\delta}\,(v_i)]}}\left(\mathbb{E}_0\left[\tilde{\delta}\left(v_{(M)}\right)^2\right] - \mathbb{E}_0\left[\tilde{\delta}\left(v_{(M-1)}\right)^2\right]\right)}_{\text{trading profits net of execution costs and priority fees}} + \underbrace{\frac{\beta}{M} R}_{\text{validation rewards}} \quad . \tag{30}$$

The function H converges to zero as M goes to infinity. If $H(2) > C$, then there exists $M \geq 2$ that satisfies (30)*. In this case, the equilibrium number of informed traders M increases with the expected blockchain validation reward $\beta\, R$ distributed to informed traders, and with the size N and elasticity θ of uninformed liquidity demand. Conversely, M decreases with the information cost C.*

The equilibrium number of informed traders characterised in Proposition 6 ensures that the profits from informed trading net of execution costs and priority fees, and blockchain validation rewards, offset the costs of acquiring information. In the equilibrium condition (30), the second term of $H(M)$, i.e., $\beta\, R/M$, represents the expected validation reward, as each trader has a β/M probability of validating the next block. The first term of $H(M)$ is

$$\kappa\, \left(\mathbb{E}_0[M\, \delta(v_{(M)})^2] - \mathbb{E}_0[M\, \delta(v_{(M-1)})^2]\right) / M$$

and it represents the expected profit from winning the auction. More precisely, at stage zero, $1/M$ is the ex-ante probability of winning the auction. The object of competition in the PGA is the adverse price impact $M\, \delta^2/\kappa$ that the informed trader avoids by winning. In a first-price sealed-bid auction with M competitors, the average winning bid corresponds to the expectation of the second highest private value. Finally, the trading volumes are adjusted by the expected execution costs and priority fees.

The equilibrium number of informed traders enhances price efficiency. Proposition 6 shows that price efficiency decreases with the cost of information C. Price efficiency increases with the magnitude of blockchain validation rewards, which offset priority fee losses, and with the size of uninformed trading, which incentivises greater liquidity supply and makes informed trading more profitable.

To study the effect of block time, or signal variance, on price efficiency, we consider the simple case where the distribution F of signals v is such that the distribution of $\tilde{\delta} = \delta/\kappa$ is uniform. The portion $\tilde{\delta}(v_i)$ of the pool traded by informed trader i in (28) decreases at a rate $1/M$, so we assume that $\tilde{\delta}(v_i)$ is uniformly distributed on an interval $[0, D/M]$, where D depends only on the maximum signal value $\overline{v}$.[13] The following result presents the equilibrium condition in this case.

COROLLARY 1: *Assume $\tilde{\delta}$ is uniformly distributed on the interval $[0, \overline{\delta}/M]$. The equilibrium condition* (30) *becomes*

$$C \leq \frac{\sqrt{24\, \pi\, \theta\, N\, M}}{M\, (2 + 3\, M + M^2)}\overline{\delta} + \frac{\beta}{M}\, R\,,$$

[13] $\tilde{\delta}(0) = 0$ implies that $\mathbb{E}_i[V \mid v_i = 0] = \pi$ in our model.

the condition (22) *for markets not to shut down is*

$$\overline{\delta}^2 \leq \frac{3\,\pi\,N\,M}{\theta}\,,$$

and the equilibrium liquidity supply (29) *is*

$$\kappa^\star = \sqrt{\frac{\pi\,N\,\theta}{M\,\mathbb{V}_L[\tilde{\delta}_i]}} = \frac{12}{\overline{\delta}}\,\pi\,M\,N\,\theta\,.$$

Corollary 1 shows that as the number of informed traders increases, the equilibrium liquidity supply increases,[14] and the signal variance threshold beyond which markets shut down also increases. This occurs because, as M grows, competition grows and trading volumes decline, reducing the potential losses of liquidity suppliers, who in turn increase their liquidity supply and accept more risk. Recall that the magnitude of blockchain validation rewards incentivises purchase of information and increases M, so validation rewards also increase the signal variance threshold and reduce the likelihood of market shutdown. Additionally, longer block times, i.e., larger values of $\overline{\delta}$, increase the number of informed traders. This is because longer block times increase signal variance, enhancing the profitability of informed trading and incentivizing traders to pay the cost C. However, there is a limit to this variance beyond which markets shut down.

Our findings have implications for the design of blockchain protocols. There is a tradeoff between price efficiency and liquidity supply in DEXs when setting block time. Longer block times improve price efficiency by increasing the profitability of informed trading, thereby encouraging more traders to pay the information cost C. However, longer block times also reduce liquidity supply, and there exists a threshold beyond which markets shut down. At this limit, where signal variance reaches its upper bound, price efficiency is maximized,[15] and the number of informed traders M is the integer part of the solution to

$$C = \frac{6\sqrt{2}\,\pi\,N}{2+3\,M+M^2}\overline{\delta} + \frac{\beta}{M}\,R\,.$$

Finally, when the noise in signals approaches zero ($\overline{\delta} \approx 0$), prices fully incorporate all private observable information, and the profitability of informed trading vanishes. In this case, the only incentive to pay the information cost is the blockchain validation reward. When $\beta = 0$ or $R = 0$, there is no incentive to acquire information, and the only possible equilibrium is one with no informed traders. Thus finding was originally established in Grossman and Stiglitz (1980) for traditional markets.

[14] This observation holds in a more general setup because the proportional trading volumes $\tilde{\delta}$ in (28) of informed traders in the general case decreases at a rate $1/M$ so the equilibrium supply (29) increases in M.

[15] Recall that in this case, the liquidity supply is $2\,\theta$.

VI. Conclusions

This paper studied the microstructure of blockchain-based DEXs which are shaped by the interplay of AMM rules and blockchain protocols. Priority fees, paid to validators to secure queue priority, influence both the cost of trading and the dissemination of information. Although priority fees introduce a new source of friction, they benefit DEXs by transferring speculative revenue from informed traders to validators, who secure the blockchain. This transfer reduces informed trading volumes, increases liquidity supply, and lowers trading costs for uniformed liquidity demanders. However, this transfer also reduces the informational content of prices.

We showed that block time presents a tradeoff for DEXs and can either hinder or enhance market efficiency. On the one hand, we show, both theoretically and empirically, that price efficiency in blockchain-based markets is constrained by the slot structure, with information only revealed at the end of each slot (e.g., every 12 seconds in Ethereum). Moreover, long block times reduce liquidity supply because providers face prolonged exposure to adverse selection risk. On the other hand, block time allows liquidity demand to aggregate, generating higher fee revenue and deeper liquidity.

Next, we showed that while the impact of discrete information release on market efficiency is unclear, external markets with continuous price discovery may hinder DEX efficiency. Prices from these markets are signals for informed traders, which discourage liquidity providers from participating in DEXs, even with priority fees, to avoid adverse selection risk.

Future work will compare the predicted stylised facts of DEXs with empirical observations from blockchain data. Some cryptocurrencies are traded exclusively on blockchains. This provides a unique setting to study DEX microstructure without the influence of traditional trading venues. Such studies can assess the efficiency of DEXs empirically and theoretically. A further issue to examine is whether the transparency of memory pools and blockchains restricts liquidity providers. Specifically, it is unclear if this transparency hinders their ability to unwind or rebalance positions effectively. Finally, future work should study the impact of MEV and layer 2 blockchains on the microstructural properties of DEXs.

Appendix A. Priority gas auctions in Ethereum

The Ethereum blockchain launched in 2015 with a proof-of-work (PoW) consensus mechanism. Under PoW, nodes compete to solve complex computational puzzles to earn the right to add the next block. This process made block times random. On 15 September 2022, Ethereum transitioned to proof-of-stake (PoS) with the "merge". Under PoS, participants stake ETH-the native digital currency on Ethereum-to become validators, which eliminates the need for computational puzzles. Block building in PoS is deterministic, with time divided into fixed 12-second slots, each producing a new block.

Next, we describe the mechanics of priority gas auctions in Ethereum, which form the basis of our modelling assumptions. There are three stages in the lifecycle of transactions on the Ethereum blockchain: (i) submission, where an agent sets the transaction details and a gas fee (base fee and priority fee); (ii) storage in the memory pool, where the transaction awaits selection by a validator; and (iii) inclusion in a block, or mining, which corresponds to the execution of the transaction.

A key feature of the Ethereum protocol is the *account nonce*, a counter assigned to each agent's account that tracks the number of executed transactions, i.e., the number of transactions included in previous blocks. The nonce prevents replay and double-spending attacks Vujičić, Jagodić, and Ranić (2018). Let n denote an agent's current account nonce. When submitting transactions, the agent must specify a nonce for each transaction, and it determines its eligibility for execution: (i) transactions with a nonce strictly smaller than n are immediately rejected by the network, (ii) transactions with nonce $n+1$ are eligible for inclusion in the next block, and (iii) transactions with a nonce strictly greater than $n+1$ are placed in a queue and remain pending until all lower-nonce transactions are executed.

The nonce mechanism also enables agents to cancel and replace a transaction. While transactions confirmed by the network cannot be effectively canceled, an agent can modify transactions which are in the memory pool, before they are included in a block, by submitting a new one with the same nonce but with a higher priority fee. Ethereum builders, who maximise revenue, will always select the transaction with the highest gas fee.

Agents might attempt to manipulate this mechanism by submitting a transaction with the same nonce but with a deliberately failing execution (e.g., setting a buy price limit at zero), followed by a second transaction with the intended original transaction but with lower gas fees. However, failed transactions still incur gas costs. Consequently, agents can only revise gas fees upward, a key assumption in our model.

Appendix B. Proofs

Appendix A. Proof of Lemma 1

Consider the prices to buy and sell a quantity δ in (2). To guarantee no profitable roundtrip arbitrage, we require for all $y > 0$ and for all $0 < \delta < y$ that

$$\underbrace{\frac{\Phi(y) - \Phi(y+\delta)}{\delta}}_{\text{price sell } \delta} \leq -\Phi'(y) \leq \underbrace{\frac{\Phi(y-\delta) - \Phi(y)}{\delta}}_{\text{price buy } \delta},$$

which implies that Φ must be convex.
Next, assume that the initial reserves in an AMM are $\{\Phi(y_0), y_0\}$ so the initial wealth of the liquidity supplier is

$$\Phi(y_0) + y_0\, V_0 = \Phi(y_0) - y_0\, \Phi'(y_0)\,.$$

Following a trading volume δ, the new liquidation value is V and the reserves are $y = y_0 + \delta$. Thus, the wealth of the liquidity supplier becomes

$$\begin{aligned}(\Phi(y) + y\, V) - (\Phi(y_0) + y_0\, V_0) + \pi\, \delta &= \Phi(y) - y\, V - (\Phi(y_0) - y_0\, V_0) + \pi\, \delta \\ &= \Phi(y) - \Phi(y_0) - (y_0 + \delta)\; V + y_0\, V_0 + \pi\, \delta \\ &= y_0\; (V - V_0) + \Phi(y) - \Phi(y_0) - \delta\, V_0 + \pi\, \delta\,,\end{aligned}$$

proving the result. □

Appendix B. Proof of Proposition 1

The PGA is modelled as a first-price online auction with a hard close at the end of the blockchain slot, i.e., the auction runs for a fixed duration T. Using backward induction, we show that late bidding, i.e., submitting priority fees immediately before the end of the slot, is the dominant strategy for competitive informed traders.
Consider a period $[T - \tau, T]$, where $\tau > 0$ is small, which we refer to as the final period. In the final period, each trader has at most one opportunity to revise their priority fee before the auction ends and the block is created. Since priority fees can only be revised upward, let $\widetilde{\varphi} \geq \underline{\delta}$ denote the highest priority fee at the end of round one, i.e., at the end of the first period $[0, T - \tau]$. Thus, the final stage of the auction is a first-price sealed-bid auction with public reserve price $\widetilde{\varphi}$. This auction is a slight variation of the auction analysed in Section III.B and solved in Appendix B.C. Following similar arguments, we obtain the following result.

PROPOSITION 7: *The equilibrium priority fee of the second stage when the current maximum*

priority fee at time $T-\tau$ is $\widetilde{\varphi}$ is

$$\varphi_i^\star = \frac{2}{\kappa}\left(\delta_i^2 - 2\,\frac{\int_{\widetilde{\delta}}^{\delta_i} x\,G\left(x\right)dx}{G\left(\delta_i\right)}\right)1_{2\,\delta_i^2/\kappa\geq\widetilde{\varphi}}\,, \tag{B1}$$

where $2\,\widetilde{\delta}^2/\kappa=\widetilde{\varphi}$. In particular, the equilibrium priority fee is increasing in the reserve priority fee φ_*

$$\partial_{\widetilde{\varphi}}\varphi^\star = \frac{4\,\widetilde{\varphi}}{\kappa}\,\frac{G\left(\widetilde{\varphi}\right)}{G\left(\delta_i\right)} > 0\,, \tag{B2}$$

and trader i's expected profit is decreasing in $\widetilde{\varphi}$

$$\partial_{\widetilde{\varphi}}\mathbb{E}[W_i] = -\frac{4\,\widetilde{\varphi}}{\kappa}\,G\left(\widetilde{\varphi}\right) > 0\,. \tag{B3}$$

Next, consider the behaviour of informed traders during the online auction of round one, i.e., over the interval $[0, T-\tau]$. By Proposition 7 and the description of the PGA in Appendix A, any bid on the priority fee can only increase the current highest bid $\widetilde{\varphi}$. Consequently, no trader has an incentive to bid early in round one because it would decrease their expected terminal wealth; see (B3). Thus, the priority fee remains constant and equal to the starting bid set by the blockchain protocol, which corresponds to the mandatory base fee for inclusion in a block (normalised to zero in our model). Therefore, each informed trader finds it optimal to delay bidding until the last moment. □

Appendix C. Proof of Proposition 2

The first-order condition (FOC) derived from the optimisation problem in (14) is

$$\frac{1}{\varphi'\left(\varphi^{-1}\left(\varphi_i\right)\right)}\,g\left(\varphi^{-1}\left(\varphi_i\right)\right)\times\left(-\varphi_i+\frac{2\,\delta_i^2}{\kappa}\right)-G\left(\varphi^{-1}\left(\varphi_i\right)\right)\,.$$

In equilibrium, trader i finds it optimal to adopt the same strategy φ, so $\varphi^{-1}\left(\varphi_i\right)=\delta_i$, and the FOC becomes

$$\varphi'\left(\delta_i\right)G\left(\delta_i\right)+g\left(\delta_i\right)\varphi_i = g\left(\delta_i\right)\left(2\,\delta_i^2\Big/\kappa\right),$$

or equivalently

$$\varphi\left(\delta_i\right)G\left(\delta_i\right) = 2\int_{\underline{\delta}}^{\delta_i}\left(x^2\Big/\kappa\right)g\left(x\right)\,dx = \frac{2}{\kappa}\left[\delta_i^2\,G\left(\delta_i\right)-2\int_{\underline{\delta}}^{\delta_i}x\,G\left(x\right)\,dx\right],$$

proving the result. □

Appendix D. Proof of Proposition 3

Use the optimal priority fee (15) in the objective (16) to write the expected wealth of trader i as

$$\mathbb{E}\left[W_i\right] = \frac{1}{\kappa}\left(4\int_{\underline{\delta}}^{\delta_i} x\, G\left(x\right) dx + \kappa\,\delta_i\, V_i - 3\,\delta_i^2\right) .$$

The optimal trading volume is the solution of $\partial_{\delta_i}\mathbb{E}\left[W_i\right] = 0$ or

$$0 = \frac{1}{\kappa}\left(4\,\delta_i\, G\left(\delta_i\right) + \kappa\, V_i - 6\,\delta_i\right) . \tag{B4}$$

Recall that, in equilibrium, G is the distribution of trading volumes pinned down by the equilibrium trading volume function δ, so

$$G\left(\delta_i\right) = \int_{\underline{\delta}}^{\delta_i} \frac{f\left(\delta^{-1}\left(x\right)\right)}{\delta'\left(\delta^{-1}\left(x\right)\right)} dx = \int_0^{v_i} f\left(y\right)\, dy = F\left(v_i\right) .$$

Rearranging (B4) one obtains

$$0 = 4\,\delta_i\, F\left(v_i\right) + \kappa\, V_i - 6\,\delta_i \implies \delta_i^\star = \delta\left(v_i\right) = \kappa\,\frac{V_i}{2\,\left(3 - 2\,F\left(v_i\right)\right)} .$$

□

Appendix E. Proof of Proposition 4

The first order condition from optimisation problem (19) of the liquidity supplier is

$$0 = \pi\, N\,\theta/\kappa^2 - 2\,\kappa\,\mathbb{V}_{\mathrm{L}}[\tilde{\delta}_i] ,$$

which provides the optimal liquidity depth (20) of the AMM. Thus, the wealth of the liquidity supplier is

$$\begin{aligned}\mathbb{E}_{\mathrm{L}}\left[W_L\right] &= \left(\pi\, N \,-\, \sqrt{2\,\pi\, N\,\theta\,\mathbb{V}_{\mathrm{L}}[\tilde{\delta}_i]}\right) - \sqrt{2\,\pi\, N\,\theta\,\mathbb{V}_{\mathrm{L}}[\tilde{\delta}_i]} \\ &\quad \pi\, N - 2\,\sqrt{2\,\pi\, N\,\theta\,\mathbb{V}_{\mathrm{L}}[\tilde{\delta}_i]} ,\end{aligned}$$

proving the result. □

Appendix F. Proof of Proposition 6

The wealth of trader i when they win or lose the PGA while M informed traders are competing is given in (25) and (26). At stage zero, the private signals have not been observed yet, so the expected validation reward is equivalent when trader i wins or loses the auction, and it corresponds

to the distribution of the highest observed signal among M observations, thus

$$\mathbb{E}_0\left[W_i\left(\text{win}\right)\right]=\mathbb{E}_0\left[W_i\left(\text{lose}\right)\right]+\mathbb{E}_0\left[-\varphi\left(v_{(M)}\right)+M\,\delta_i^2/\kappa\right]\,.$$

Moreover, the probability of observing the highest signal and winning the auction is $1/M$, so the expected wealth of trader i, when they pay the cost C is

$$\begin{aligned}&\frac{M-1}{M}\,\mathbb{E}_0\left[W_i\left(\text{lose}\right)\right]+\frac{1}{M}\,\mathbb{E}_0\left[W_i\left(\text{win}\right)\right]\\=&\mathbb{E}_0\left[W_i\left(\text{lose}\right)\right]+\frac{1}{M}\,\mathbb{E}_0\left[-\varphi\left(\delta\left(v_{(M)}\right)\right)+M\,\delta\left(v_{(M)}\right)^2/\kappa\right]\,,\end{aligned}$$

where $v_{(M)}$ denotes the highest observed signal, whose cumulative distribution function is $F(\cdot)^M$. If trader i does not pay C to gather private information and participate in blockchain validation, then her expected wealth is

$$\mathbb{E}_0\left[W_i\left(\text{lose}\right)\right]+C-\frac{\beta}{M}\,\left(\mathbb{E}_0\left[\varphi\left(\delta\left(v_{(M)}\right)\right)\right]+R\right)\,,$$

because she does not pay C but she also loses the expected validation reward. Thus, trader i invests in informed trading whenever

$$C<\frac{1}{M}\,\mathbb{E}_0\left[-\varphi\left(\delta\left(v_{(M)}\right)\right)+M\,\delta\left(v_{(M)}\right)/\kappa\right]+\frac{\beta}{M}\,\left(\mathbb{E}_0\left[\varphi\left(v_{(M)}\right)\right]+R\right)\,.$$

Using (27), this condition can be written as

$$C<\frac{1}{M}\,\mathbb{E}_0\left[\frac{2\,M}{\kappa}\frac{\int_{\underline{\delta}}^{\delta\left(v_{(M)}\right)}x\,G\left(x\right)^{M-1}\,dx}{G\left(\delta\left(v_{(M)}\right)\right)^{M-1}}\right]+\frac{\beta}{M}\,R\,,$$

and the equilibrium condition corresponds to equality in the equation above. Next, we prove that

$$2\,\mathbb{E}_0\left[\frac{\int_{\underline{\delta}}^{\delta\left(v_{(M)}\right)}x\,G\left(x\right)^{M-1}\,dx}{F\left(v_{(M)}\right)^{M-1}}\right]=\mathbb{E}_0\left[\delta^2\left(v_{(M-1)}\right)\right]-\mathbb{E}_0\left[\delta^2\left(v_{(M)}\right)\right]\,.\tag{B5}$$

To prove the above equality, we derive the expressions for the expected trading volumes corresponding to the highest and second highest private signals, which are distributed according to, respectively, $F(\cdot)^M$ and $M\,F(\cdot)^{M-1}-(M-1)\,F(\cdot)^M$. Using integration by parts, write

$$\begin{aligned}\mathbb{E}_0\left[\delta^2\left(v_{(M)}\right)\right]=&\int_0^{\overline{v}}\delta^2\left(x\right)\,d\left(F\left(x\right)^M\right)\,dx\\=&\overline{\delta}^2-2\int_0^{\overline{v}}\delta\left(x\right)\,\delta'\left(x\right)\,F\left(x\right)^M\,dx\,,\end{aligned}\tag{B6}$$

and

$$\mathbb{E}_0\left[\delta^2\left(v_{(M-1)}\right)\right] = \int_0^{\overline{v}} \delta^2(x)\, d\left(M\, F(x)^{M-1} - (M-1)\, F(x)^M\right) dx$$
$$= \overline{\delta}^2 + 2\int_0^{\overline{v}} \delta'(x)\, \delta(x)\, \left((M-1)\, F(x)^M - M\, F(x)^{M-1}\right) dx\,, \qquad \text{(B7)}$$

proving (B5). Finally, use the equilibrium liquidity supply (29) to obtain the equilibrium condition (30) in the statement of the result.

Next, to show that $H(M)$ converges to zero as M goes to inifinity, first write

$$\tilde{\delta}(x) = \frac{V(x) - \pi}{2\left(1 + M\left(1 - F(x)^{M-1}\right)\right)} \leq \frac{\overline{V} - \pi}{2\,(1+M)} \leq \frac{\overline{V} - \pi}{2\,M}\,,$$

for all $x \leq \overline{v}$, so $\sqrt{\frac{\pi\, N\, \theta}{M\, \mathbb{V}_{\mathrm{L}}[\tilde{\delta}(v_i)]}}$ grows in M at most at a rate $\sqrt{M}$. Moreover, use (B6), (B7), and the fact that the trading volume is finite, to obtain that $\mathbb{E}_0\left[\tilde{\delta}^2\left(v_{(M)}\right)\right] - \mathbb{E}_0\left[\tilde{\delta}^2\left(v_{(M-1)}\right)\right]$ converges at a rate $M\, a^M$ for $a < 1$, so the first term of $H(M)$ converges to zero as M goes to infinity. It is straightforward to see that $\beta\, R/M$ also converges to zero because β and R are fixed, proving the result. □

Appendix G. Proof of Corollary 1

To obtain the result, it is enough to write the expectation of the squared highest trading volume as

$$\mathbb{E}_0\left[\tilde{\delta}^2\left(v_{(M)}\right)\right] = \int_0^{\overline{\delta}/M} x^2 d\left(F(x)^M\right) dx = \frac{\overline{\delta}^2}{M\,(2+M)}$$

and

$$\mathbb{E}_0\left[\tilde{\delta}^2\left(v_{(M-1)}\right)\right] = \int_0^{\overline{\delta}/M} x^2 d\left(M\, F(\cdot)^{M-1} - (M-1)\, F(\cdot)^M\right) dx = \frac{M-1}{M\,(2+3\,M+M^2)}\overline{\delta}^2\,.$$

□

Appendix C. Equilibrium priority fees and trading volumes without impact approximation

This section solves the game described in Sections III and IV under the assumption that each trader's impact is determined by their trading signal.

If trader i wins the auction, i.e., if $\varphi_i > \varphi_j$, her buy order is executed first, and her execution price is $V_0 - \delta_i/\kappa = -\delta_i/\kappa$; see (2). Conversely, if trader j's order is executed first, i.e., if $\varphi_i < \varphi_j$, then trader i's execution price is $\delta_i/\kappa + 2, \delta_j/\kappa$ instead; see (3). The corresponding wealth expressions for trader i in both cases are given by

$$\begin{cases} W_i\left(\text{win}\right) = & -\varphi_i - \delta_i\ \left(\delta_i/\kappa + \pi\right) \quad + \delta_i\, V \\ W_i\left(\text{lose}\right) = & -\delta_i\ \left(\delta_i/\kappa + 2\,\delta_j/\kappa + \pi\right) \quad + \delta_i\, V\,. \end{cases} \tag{C1}$$

In contrast to the model in the main text, the adverse price impact $2, \delta_j/\kappa$ from losing priority is now a random variable. The expected wealth of trader i is given by

$$\mathbb{E}_i\left[W_i\right] = \int_0^{\overline{v}} 1_{\varphi_i > \varphi_j}\left(-\varphi_i + 2\,\delta_i\,\delta_j/\kappa\right)\ f\left(x\right)\ dx - \delta_i^2/\kappa - 2\,\delta_i\,\mathbb{E}_i\left[\delta_j\right]/\kappa + \delta_i\ \left(V_i - \pi\right)\,, \tag{C2}$$

where $\mathbb{E}i\left[\delta j\right]$ represents trader i's expectation of trader j's trading volume, conditional on their own private information.

As in the main model, one can show that $\partial_{\delta_i\, v_i} \neq 0$, implying that the optimal trading volume depends on the private signal, and it is thus a random variable. Let g denote its density and G its cumulative distribution function. Similarly, $\partial_{\varphi_i\, \delta_i} \neq 0$, so the priority fee is a function of the trading volume or equivalently a function of the private signal. Trader i determines the optimal priority fee by solving

$$\sup_{\varphi_i}\left\{\int_0^{\overline{v}} 1_{\varphi_i > \varphi_j}\left(-\varphi_i + 2\,\delta_i\,\delta_j/\kappa\right)\ f\left(x\right)\ dx\right\}\,. \tag{C3}$$

Unlike the main model, the problem (C3) corresponds to a symmetric first-price sealed-bid common value auction, where the item's value is $2\,\delta_i\,\delta_j/\kappa$. Common value auctions typically involve a winner's curse, where bidders risk overestimating the item's value. Here, trader i does not consider the naive expectation of the item's value $2\,\delta_i, \delta_j/\kappa$, but instead considers the expected value of the item conditional on the event of winning; see Chapter 4 of Menezes and Monteiro (2005) for similar problems. The optimal priority fee is characterised in the following result.

PROPOSITION 8: *The equilibrium priority fee is*

$$\varphi_i^\star = \frac{2}{\kappa}\left(\delta_i^2 - 2\,\frac{\int_{\underline{\delta}}^{\delta_i} x\, G\left(x\right) dx}{G\left(\delta_i\right)}\right)\,. \tag{C4}$$

The priority fee increases in the trading volume.

Proof. Assume trader j uses the priority fee bidding strategy φ. The expected payoff of trader i is

$$\int_0^{\varphi^{-1}(\varphi_i)} \left(-\varphi_i + 2\,\delta_i\,x/\kappa\right)\, g\left(x\right)\, dx = -\varphi_i\, G\left(\varphi^{-1}\left(\varphi_i\right)\right) + 2\,\delta_i/\kappa \int_0^{\varphi^{-1}(\varphi_i)} x\, g\left(x\right)\, dx\,.$$

The first-order condition from problem (C3) is

$$\frac{1}{\varphi'\left(\varphi^{-1}\left(\varphi_i\right)\right)}\, \left(-\varphi_i + 2\,\delta_i\,\varphi^{-1}\left(\varphi_i\right)\, \Big/ \kappa\right) g\left(\varphi^{-1}\left(\varphi_i\right)\right) - G\left(\varphi^{-1}\left(\varphi_i\right)\right) = 0\,.$$

In equilibrium, trader i employs the same strategy, in which case $\varphi^{-1}\left(\varphi_i\right) = \delta_i$. This gives

$$g\left(\delta_i\right)\left(2\,\delta_i^2\Big/\kappa\right) = G\left(\delta_i\right)\,\varphi'\left(\delta_i\right) + \varphi\left(\delta_i\right)\, g\left(\delta_i\right) \implies G\left(\delta_i\right)\,\varphi\left(\delta_i\right) = \int_{\underline{\delta}}^{\delta_i} g\left(x\right)\left(2\,x^2\Big/\kappa\right)\, dx\,.$$

Applying integration by parts yields the result in (C4). □

In equilibrium, the priority fee as a function of trading volume take a similar for to that in Section III. However, the relationship between trading volume and the trading signal differs, and the distribution of equilibrium trading volumes is different from that in (13). For consistency, we continue to denote the distribution of the trading signal by g, despite it now representing a different distribution. In what follows, we employ the notation

$$V_i(v) = \mathbb{E}_i\left[V \mid v_i = v\right] = \int \mathbb{E}\left[V \mid v_i = v, v_j = x\right]\, f\left(x\right)\, dx \quad \text{and} \quad V_i'(v) = \partial_v V_i(v)\,.$$

The next result characterises the equilibrium trading volume and demonstrates that it retains the same properties as those established in Proposition 3 and the main model in the text.

PROPOSITION 9: *The equilibrium trading volume is*

$$\delta_i^\star = \delta\left(v_i\right) = e^{F(v_i)}\left(\underline{\delta} + \frac{\kappa}{2}\int_0^{v_i} e^{-F(x)} V_i'(x)\, dx\right)\,, \tag{C5}$$

where $\underline{\delta} = \frac{\kappa}{2}\left(V_i(0) - \pi\, e^{-1}\right) + \frac{\kappa}{2}\int_0^{\overline{v}} e^{-F(x)} V_i(x)\, f(x)\, dx > 0$*. The trading volume is an increasing and continuously differentiable function of the private signal.*

Proof. Use the priority fee (C4) to write trader i's wealth (C2) as

$$\mathbb{E}_i\left[W_i\right] = \frac{4}{\kappa}\int_{\underline{\delta}}^{\delta_i} x\, G\left(x\right)\, dx - \frac{2}{\kappa}\,\delta_i \int_{\underline{\delta}}^{\delta_i} G\left(x\right)\, dx - \delta_i^2/\kappa - 2\,\delta_i\,\mathbb{E}_i\left[\delta_j\right]/\kappa + \delta_i\,\left(V_i - \pi\right)\,.$$

The first-order condition for the optimal trading volume is

$$0 = \frac{2}{\kappa}\delta_i\,\left(G\left(\delta_i\right) - 1\right) - \frac{2}{\kappa}\int_{\underline{\delta}}^{\delta_i} G\left(x\right)\, dx - 2\,/\kappa \int_0^{v_i} \delta_j\left(x\right)\, f\left(x\right)\, dx + V_i - \pi\,.$$

In equilibrium, both traders employ the same trading volume function δ. Use $G(x) = F\left(\delta^{-1}(x)\right)$ and the first-order condition to write the following equation for δ:

$$0 = -\frac{2}{\kappa}\delta(v_i) - \frac{2}{\kappa}\int_{v_i}^{\overline{v}} \delta(y)\ f(y)\ dy + V_i(v_i) - \pi\,.$$

This yields the boundary condition $\delta(\overline{v}) = \kappa\left(V_i(\overline{v}) - \pi\right)/2$. Differentiating with respect to v_i gives the ordinary differential equation

$$\delta'(v_i) = \delta(v_i)\ f(v_i) + \frac{\kappa}{2}V_i'(v_i)\ ,$$

whose solution is

$$\delta(v_i) = e^{F(v_i)}\left(c + \frac{\kappa}{2}\int_0^{v_i} e^{-F(x)}V_i'(x)\,dx\right)\ .$$

The boundary condition at $v_i = 0$ gives $c = \underline{\delta} = \delta(0)$ and the boundary condition at $v_i = \overline{v}$ gives

$$\underline{\delta} = \frac{\kappa}{2}\left(V_i(0) - \pi\, e^{-1}\right) + \frac{\kappa}{2}\int_0^{\overline{v}} e^{-F(x)}V_i(x)\,f(x)\,dx\,,$$

which is positive by Assumption 2. Finally, the derivative of the equilibrium trading volume is

$$\delta'(v_i) = \frac{\kappa}{2}V_i'(v_i) + e^{F(v_i)}\left(\underline{\delta} + \frac{\kappa}{2}\int_0^{v_i} e^{-F(x)}V_i'(x)\,dx\right)$$

which is positive by Assumption 1. □

Appendix D. Illustration of the model with M traders and decision to purchase information

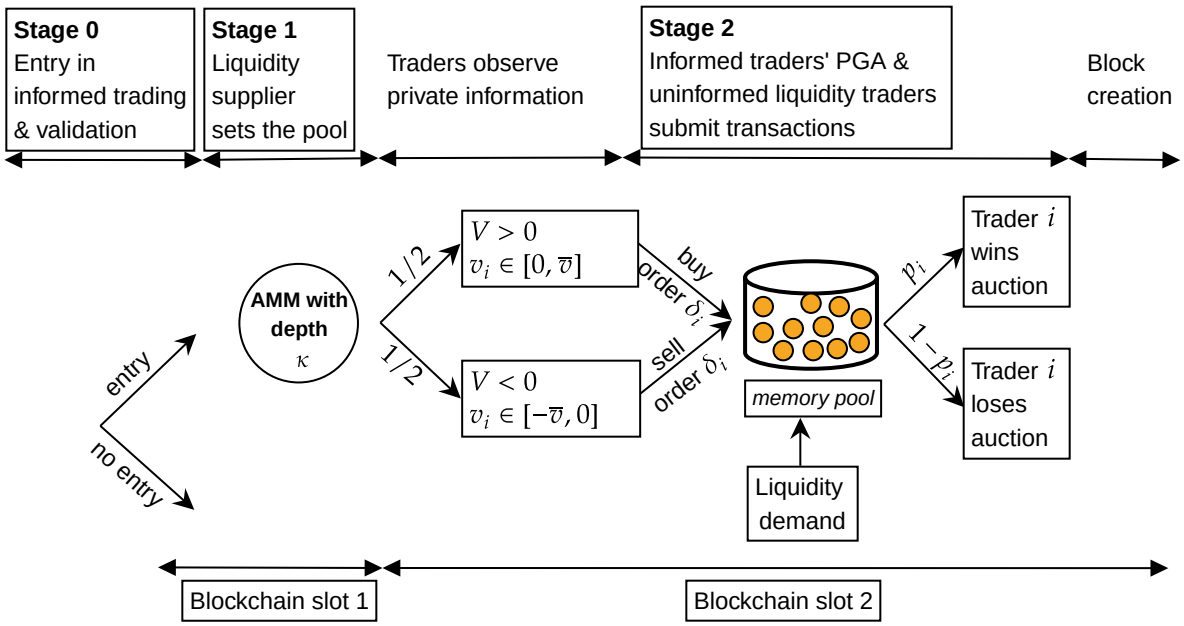


Figure 5. Sequence of events.

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Notes